Journal of Applied Technology and Innovation
Vol. 10, Issue 2, 2026, pp. 42-56
e-ISSN:2600-7304-ISSN
doi: https://doi.org/10.65136/jati.v10i2.336

Robust Product Design: An Overview of Quality Engineering and Optimization Approaches in Manufacturing Systems

Amir Parnianifard[1*], **Che Munira Che Razali**[2]

[1]Glasgow College, University of Electronic Science and Technology of China, 11730 Chengdu, China
[2]Politeknik Premier Sultan Salahuddin Abdul Aziz Shah, 40150 Shah Alam, Selangor, Malaysia
*Corresponding author: amir.parnianifard@glasgow.ac.uk

Received: 2026-04-18; Accepted: 2026-02-20; Published: 2026-06-16

Abstract

One of the main technological and economic challenges for engineers is designing high-quality products in manufacturing processes. Most of these processes involve many variables, including controllable (design) and uncontrollable (noise) factors. The Robust Design (RD) method employs a collection of mathematical and statistical tools to investigate these variables while minimizing computational effort. RD aims to achieve high product quality from the customers' perspective while maintaining an acceptable profit margin. This paper provides an overview of RD concepts, methodologies, and optimization approaches, with particular emphasis on their applications in manufacturing systems. The basic concepts of the quality loss function, orthogonal array, and crossed array design are explained. Furthermore, two classifications are presented according to RD methodology: the first based on different types of factors and the second based on different types of data. These classifications play an important role in determining the number of required experimental replications and selecting appropriate data analysis methods. In addition, the integration of RD with advanced optimization techniques, particularly hybrid model-based and metamodel-based approaches, is discussed to demonstrate how these methods can improve design efficiency while reducing computational cost in manufacturing process design and optimization.

Keywords: *Robust Design, Taguchi Method, Product Design, Manufacturing Systems, Quality Engineering, Quality Loss Function.*

1. Introduction

In a new comprehensive world with varieties of industries, rapid progress in technology causes all companies and organizations in all types of industries to improve and adjust their processes according to the latest alterations. Moreover, in each company, flexibility is an essential matter for preserving their productivity, and efficiency and keeping their survival among other rivals. So, companies must remain in the best condition (flexible) despite rapid progress in technology and change in product specifications. Therefore, most techniques and methods have been presented to help engineers designing the company's processes to achieve the highest quality at least costs. Nowadays, one of the main techniques that have been applied to achieve the aforesaid purpose is quality engineering. Quality engineering is an interdisciplinary science that is concerned with not only producing satisfactory products for customers but also reducing the total loss (manufacturing cost plus quality loss). The RD is one of the main tools that have been used in quality engineering (S. Park & Antony, 2008).

Most processes are affected by external uncontrollable factors in real conditions, which cause quality characteristics to be far from ideal points and have variation. Figure 1 illustrates an overview of manufacturing processes with input (also called design factors), output (also called response factors), and noise factors (also called environmental factors). In process robustness studies, it is desirable to minimize the influence of noise factors and uncertainty on the process and simultaneously determine the levels of input and control factors that optimize the overall responses, or in another sense, optimizing product and process which are minimally sensitive to the various causes of variance.

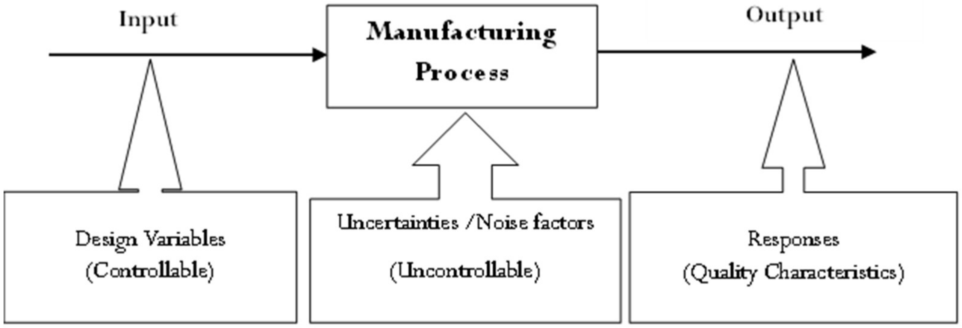

Figure 1. Manufacturing process under effect of three set of variables.

(Phadke, 1989) has defined some traits for the RD method in manufacturing systems, consisting of:

- Making product performance robust against raw material variation. So, it allows using the wide grade of materials and their components.
- Making product designs insensitive to manufacturing variation to reduce labor and material costs for rework and scrap.
- Designing the product least sensitive to the variation in the operating environment to enhance reliability and decrease operating costs.
- Using a new structure of process development, engineering time is used most productively.

This paper aims to provide an overview of robust design concepts, quality engineering principles, and optimization approaches, with particular emphasis on their applications in manufacturing systems. The paper discusses the role of RD in product and process design and highlights its contribution to improving quality and mitigating the effects of uncontrollable variations. Furthermore, the integration of RD with advanced optimization techniques, particularly hybrid model-based and metamodel-based approaches, is reviewed to demonstrate how these methods can improve design efficiency while reducing computational cost. Overall, the paper emphasizes the advantages of RD and its potential to enhance the performance and reliability of manufacturing processes.

The rest of this paper is organized as follows. Section 2 provides basic information on robust design methodology. In section 3 the application of robust design in different manufacturing systems is reviewed among studies in literature when combined with two types of model-based and metamodel-based optimization approaches. Section 4 presents a brief discussion of the strength and weaknesses points of RD. This paper is concluded in section 5.

2. Basics of Robust Design (RD)

The robust design (RD) methodology was introduced by Genichi Taguchi after World War II and has since become a key approach in quality engineering and experimental design. It emphasizes improving product and process quality by reducing the effects of variability without necessarily eliminating its sources, focusing on performance consistency around target values. Robust design is commonly implemented as an off-line quality control method to enhance productivity and process stability. Its main principles include parameter design, minimization of variability, and efficient experimentation using orthogonal arrays and signal-to-noise (SN) ratios. SN ratios are used to measure performance quality under different objectives, typically classified as larger-the-better, smaller-the-better, and nominal-the-best (S. Park, 1996; S. Park & Antony, 2008; Parnianifard, Azfanizam, Ariffin, & Ismail, 2019c; Phadke, 1989).

2.1 Quality Loss Function (QLF)

In manufacturing systems, processes are often affected by uncontrollable factors that lead to variability and deviation from desired performance. Taguchi's robust design aims to reduce the impact of these noise factors by minimizing quality loss and improving process stability, thereby enhancing quality, reducing cost, and shortening development time. It focuses on selecting optimal design and control factors that make performance less sensitive to variation. The concept is commonly supported by the quality loss function, which quantifies deviation from target performance and balances the trade-off between mean and variability in quality characteristics (Nha et al., 2013; S. Park & Antony, 2008; Simpson et al., 2001). Figure 2 depicts the graphical concepts of expected QLF on the classification of quality characteristics into three different types of NTB, STB, and LTB.

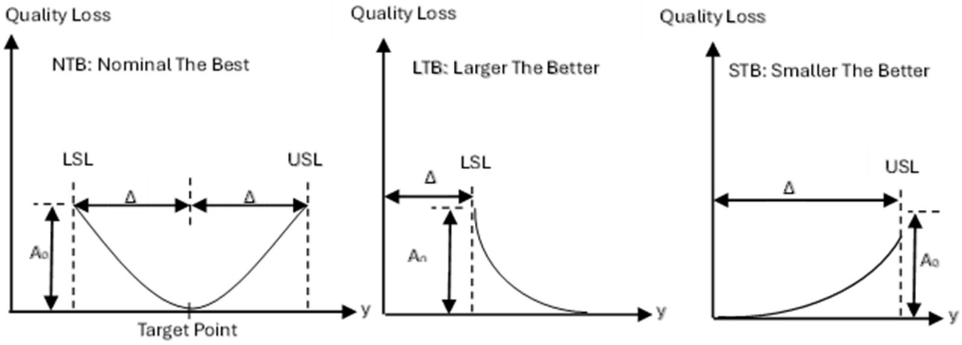

Figure 2. The expected loss functions for three types of quality characteristics.

In addition, QLF based on Taguchi's approach for all three types of quality characteristics is presented in Eqs. (1)-(3):

NTB $$L(y) = C_0[(\mu - T)^2 + \sigma^2] \tag{1}$$

STB $$L(y) = C_0[\mu^2 + \sigma^2] \tag{2}$$

LTB $$L(y) = C_0[(\frac{1}{\mu^2})(1 + 3\sigma^2/\mu^2)] \tag{3}$$

where μ , σ^2, T respectively are quality characteristic mean, variance, and target and C_0 is loss coefficient. The value of C_0 is computed by $\frac{A_0}{\Delta^2}$ for NTB and STB and $A_0\Delta^2$ for LTB. The quality loss coefficient C_0 can be determined based on information about the losses in monetary terms caused by falling outside the customer tolerance. The coefficient C_0 plays an important role to make the expected loss function in monetary loss scales. In addition, A_0 is introduced as a cost of repair or replacement when the quality characteristic performance has a distance Δ from the target point (Phadke, 1989).

(Sharma et al., 2007) have proposed the same formula for all three types of quality characteristics with more simplicity in the relevant formulation. Their proposed formula is based on a lack of accessing target to infinity for the LTB case, so it is unachievable. All three types of expected quality loss could be replaced by the proposed formulation as shown in Eq. (4):

$$Q = C_0[\mu^2(1 - \alpha) + \sigma^2] \tag{4}$$

where α is equal to $\frac{T}{\mu}$ when $0 \leq \alpha \leq m$ and m is a large number. The amount of α could be defined by the decision maker and T is a target point for the quality of the characteristic. For different values of α the expected loss represents different expected losses for each type of NTB, LTB, or STB. This value shows the shifting of μ to the right or left side of the target point and can be chosen as zero for STB type, a large number of more than one for LTB type, and 1 for NTB. But it is strongly recommended that the target point and specially α does not need to be a large number or infinity for LTB cases, but it just needs to be significantly greater than one. In (Sharma et al., 2007) and (Sharma & Cudney, 2011) have recommended that in the case of LTB the magnitude of α needs to significantly greater than one but not necessarily a large number or infinity, and they suggested $\alpha = 2$ is appropriate to be employed in practice. In (Parnianifard, Azfanizam, Ariffin, & Ismail, 2019c), the application of Eq.(4) has been expanded in multi-objective engineering design problems.

2.2 Orthogonal Array (OA)

The orthogonal array (OA) is a structured experimental design method used to efficiently explore multiple factors in a reduced number of experiments. It is represented as $L_n(m^p)$, where (n) is the number of experiments, (p) is the number of factors, and (m) is the number of levels per factor. OA ensures balanced sampling by maintaining uniform coverage of factor levels and their interactions while significantly reducing the required experimental runs compared to full factorial designs. This makes it particularly useful in computer experiments and robust design applications (Koehler & Owen, 1996; Leung & Wang, 2001).

2.3 Crossed array design

Taguchi proposed a crossed design approach for arranging the experiments in a noisy environment, while the process is influenced by environmental (noise) factors (see Figure 3**.** In this arrangement, combinations of design variables are designed as an inner array (input combination), and noise factors are designed separately in the outer array. For each input combination in an inner array, all noise combinations in the outer array are experimented with, see (S. Park & Antony, 2008; Phadke, 1989).

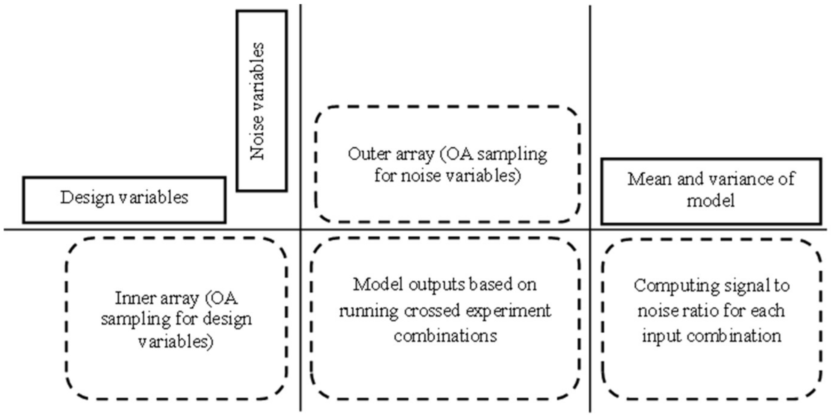

Figure 3. An overview of Taguchi crossed array design.

2.4 Types of factors and data in RD

In the RD approach, two types of factors can treat in experiments, fixed and random types, as depicted in Figure 4 (Parnianifard, Azfanizam, Ariffin, & Ismail, 2018a). When the factor levels are technically controllable, it means these factors are 'fixed'. In addition, levels in these types of factors can be re-examined and reproduced. 'Random' factors are not technically controllable. Each level does not have a technical meaning, and typical levels of a random factor cannot be re-examined and reproduced. Data in the experimental environment are usually divided into two different types discrete and continuous. Taguchi has divided each of both types into three classes, as illustrated in Figure 5. This classification plays an important role in deciding several necessary replications for experiments and determines the best method for analyzing data (S. Park, 1996; S. Park & Antony, 2008).

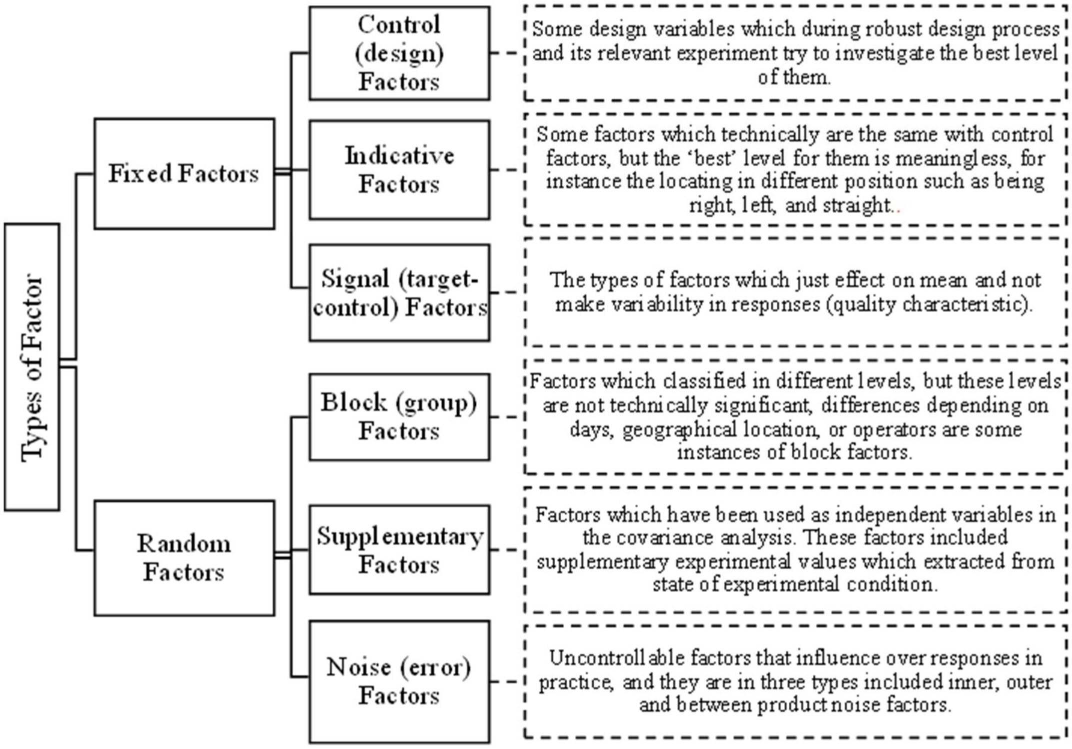

Figure 4. Different types of factors.

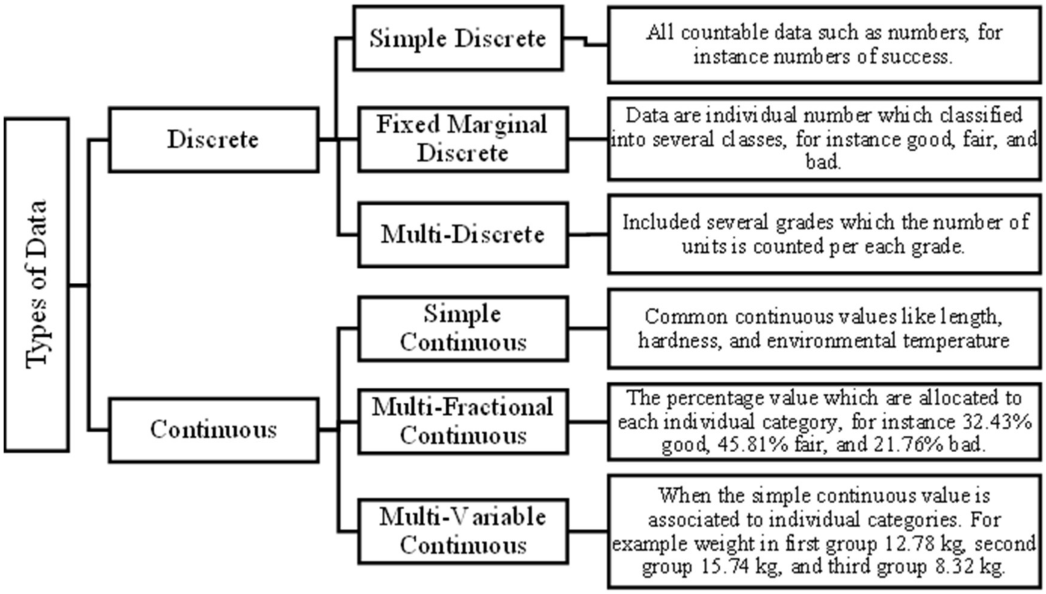

Figure 5. Types of data based on Taguchi approach.

3. Hybrid RD with Model-Based and Metamodel-Based Optimization Methods

Robust design methodology has been advocated by most researchers in lots of different studies, and it has been employed to improve the performance and quality of processes for various problems in the real world (R. H. Myers et al., 1992). Since Genichi Taguchi introduced his methods for off-line quality improvement in AT&T Bell laboratories in United State from 1980 to 1982, robust design methods have been used in many areas in the real world of engineering (Phadke, 1989). The wide application of RD particularly based on the Taguchi approach, has been attended to optimize the various manufacturing processes under noisy and uncertain conditions. Taguchi RD is a functional approach that can be combined with other associated optimization methods, particularly with two categories of robust engineering design approaches, including model-based and metamodel-based robust optimization techniques (Beyer & Sendhoff, 2007). In model-based, the original model is not expensive in terms of running experiments, and model output can be used directly in optimization. (Ben-Tal et al., 2009) have presented several model-based robust optimization methods when using different scenario sets of uncertainty in the model. However, a model-based method on separate process components including the mean and the variance has been proposed by (Kleijnen, 2010; Koehler & Owen, 1996) which is called the dual response surface method.

Many large scales and detailed models in the complex system particularly under uncertainty may be expensive to run in terms of time-consuming, computational cost, and resources (Parnianifard, Azfanizam, Ariffin, & Ismail, 2019a; Parnianifard et al., 2023, 2024). Moreover, to address such a challenge, metamodel-based methods need to be derived via combing by robust design optimization. Metamodeling is the analysis, construction, and development of the frames, rules, constraints, models, and theories applicable and useful for modeling a predefined class of problems, see (Parnianifard, Azfanizam, Ariffin, & Ismail, 2018a; Parnianifard, Azfanizam, Ariffin, Ismail, et al., 2019; Razali et al., 2020). Computation-intensive design problems are becoming increasingly common in manufacturing industries. Metamodeling techniques have been developed in many different disciplines including statistics, mathematics, computer science, and various engineering disciplines (G. Wang & Shan, 2007). Global search over design space is the main goal of model-based algorithms. Modern metamodels such as Kriging and Radial Basis Function (RBF) assisted optimization also derive global search. A metamodel or surrogate model by mathematical expression $\hat{Y} = f\widehat{(X,Z)}$ can replace with true functional relationship $Y = f(X, Z)$, where X and Z denotes respectively design and noise (uncertain) factors. The general overview of a metamodel with uncontrollable noise variables is illustrated in Figure 6.

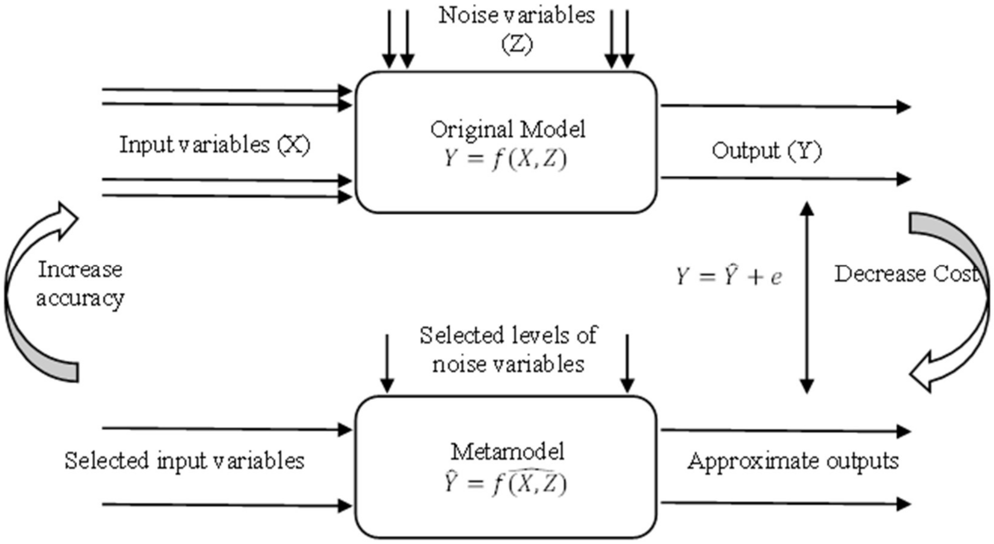

Figure 6. The viewpoint of metamodel

Different metamodeling techniques exhibit distinct performance characteristics depending on problem complexity and dimensionality. Polynomial regression models are simple and computationally efficient but often limited in capturing highly nonlinear relationships and interactions in complex manufacturing systems. In contrast, Kriging (Gaussian process) models provide strong predictive accuracy and uncertainty quantification, making them well-suited for expensive and highly nonlinear response surfaces, although their computational cost increases significantly with the number of samples and design variables. Radial Basis Function (RBF) models offer a flexible compromise, performing well in moderate- to high-dimensional problems with scattered data, but may lose accuracy when extrapolating beyond the sampled region. Overall, the choice of metamodel depends on the trade-off between computational efficiency, dimensional scalability, and the degree of nonlinearity in the underlying manufacturing process (Dellino et al., 2015; Jin et al., 2003; Simpson et al., 2001; G. Wang & Shan, 2007).

Table 1 summarizes representative studies that integrate Robust Design with model-based and metamodel-based optimization approaches. A clear trend can be observed that earlier studies predominantly rely on classical model-based strategies, such as Taguchi-based methods, response surface techniques, and mathematical programming formulations, while more recent research increasingly adopts metamodel-based approaches, particularly Kriging, radial basis functions, and machine learning-based surrogate models, to address computational complexity in large-scale and uncertainty-driven problems. Overall, the reviewed studies highlight that metamodel-based and hybrid approaches provide greater flexibility and efficiency in handling complex, noisy, and high-dimensional design problems compared to purely model-based methods. In addition, several works demonstrate the integration of evolutionary and multi-objective optimization algorithms with RD, indicating a shift toward hybrid intelligent optimization frameworks for manufacturing and engineering design applications.

Table 1. Combining RD with model-based and metamodel-based optimization methods in manufacturing systems and engineering design.

No	Ref.	Model-Based	Metamodel - Based	Optimization methods (combined with RD)
1	(Zhang & Lu, 2016)	√		Least Median Squares-Weighted Least Squares (LMS-WLS)- Fuzzy Least Squares method
2	(X. Liu et al., 2015)	√		Elfving's theorem- R-optimal designs
3	(Wu, 2015)	√		Minimizing the total quality loss (The example of an electron beam surface hardening process)
4	(Khan et al., 2015)	√		Taguchi quality loss function-Cost of Quality (COQ)
5	(Celano et al., 2014)	√		Taguchi loss function to implement Shewhart control charts monitoring
6	(Tsai & Liukkonen, 2016)	√		Fuzzy logic-based Taguchi method- ANOVA
7	(Tabrizi & Ghaderi, 2016)	√		robust mixed-integer programming mathematical model-NSGA-II
8	(An et al., 2016)	√		3-level-3-factor robust parameter design-ANOVA (for the process of antimony doped tin oxide (ATO) particles with high conductivity)
9	(C. Park & Leeds, 2016)	√		Monte Carlo simulation- heuristic approach
10	(Parnianifard, Azfanizam, Ariffin, & Ismail, 2018c)		√	Latin Hypercube- Kriging, Cross-validation, (Optimal design of PID controller)
11	(Dellino et al., 2010)		√	Latin Hypercube- RSM (the case of inventory control)
12	(Kleijnen, 2017)		√	Central Composite- Plackett Burman- Fractional Factorial- Latin Hypercube, Monte Carlo experiments Polynomial regression- Kriging
13	(Amaran et al., 2016)		√	Space-filling designs- Response surface methodology, Gradient-based methods, Discrete optimization via simulation- Sample path optimization, Direct search methods, Random search methods, Model-based methods
14	(Han & Yong Tan, 2016)		√	A Gaussian process metamodel, Monotone cubic spline, computer-aided IPTD (Integrated Parameter and Tolerance Design) approach – (The case of Design of a chemical cyclone, Manufacturing processes)
15	(Kleijnen, 2010)		√	Fractional- factorial designs, Central Composite Designs (CCDs)-First order and second-degree polynomials (RSM), Kriging, Latin Hypercube Sampling (LHS)

Table 1. Continued.

No	Ref.	Model-Based	Metamodel - Based	Optimization methods (combined with RD)
16	(Steenackers et al., 2009)		√	Response surface techniques, Monte Carlo simulations, Finite element design (The case of A slat track, structural component of an aircraft wing)
17	(Sharma & Cudney, 2011)	√		Signal-to-noise ratio based on mean squared deviation and signal-to-noise ratio based on complexity for larger-the-better characteristics
18	(Datta & Mahapatra, 2010)	√		Grey relational analysis-Quadratic mathematical model (Response Surface Model)- Taguchi's L27 (3*6) Orthogonal Array (OA) design (maximum MRR, good surface finish (Application in minimum roughness value and dimensional accuracy of the product)
19	(Erdbrügge et al., 2011)	√		Weight matrices for two and more responses to minimize the conditional mean of the loss function.
20	(Parnianifard, Azfanizam, Ariffin, & Ismail, 2018b)		√	Integrating robust design and polynomial regression metamodel and using its application in PID tuning under uncertainty
21	(Parnianifard, Azfanizam, Ariffin, Ismail, et al., 2018)		√	Integrating robust design and Kriging metamodel and using its application in PID tuning under uncertainty
22	(Parnianifard, Azfanizam, Ariffin, & Ismail, 2019b)		√	Proposing a new free-distribution robust optimization approach by integrating robust design and Kriging metamodel and showing its application in inventory management problem
23	(Peng et al., 2008)	√		Multivariate quality loss function as an extension of the Taguchi loss function-cash flow function under continuous compounding-minimizing the total cost, which is the sum of manufacturing cost and the present worth of expected quality loss
24	(Parnianifard & Azfanizam, 2020)		√	Combining robust design and Kriging metamodel and using its application in robust control of integer and fractional order multiloop PID under uncertainty
25	(Parnianifard, Chancharoen, et al., 2020)	√	√	Application of metamodels in low-dimensional constrained engineering design optimization using design and analysis of simulation experiments.
26	(Parnianifard, Fakhfakh, et al., 2020)		√	Application of surrogate-based robust simulation-optimization in robust tuning and sensitivity analysis of stochastic integer and fractional-order control systems.
27	(Parnianifard, Zemouche, Chancharoen, et al., 2020)		√	Integrating robust design, evolutionary algorithm, and metamodel in robust optimal control of five bar linkage robot manipulator.

Table 1. Continued.

No	Ref.	Model-Based	Metamodel - Based	Optimization methods (combined with RD)
28	(Parnianifard, Zemouche, Imran, et al., 2020)		√	Integrating robust design, evolutionary algorithm, and metamodel in dynamic-stochastic production/inventory control system under uncertainty.
29	(Parnianifard, Pengnoo, et al., 2021a)		√	Hybrid robust design, metamodeling, and metaheuristic in multi-transmitters placement planning
30	(Parnianifard et al., 2022)		√	A data driven approach in less expensive robust transmitting coverage and power optimization
31	(Parnianifard, Pengnoo, et al., 2021b)	√	√	Hybrid Metamodeling / Metaheuristic assisted multi-transmitters placement planning
32	(Parnianifard, Rezaie, et al., 2021)		√	Integrating robust design, evolutionary algorithm, and metamodel in dynamic-stochastic production/inventory control system under uncertainty.
33	(C. Wang et al., 2022)		√	Metamodel-based approaches for uncertainty quantification and propagation, including single and hybrid metamodels with adaptive sampling strategies to improve accuracy and reduce computational cost.
34	(Ling et al., 2022; L. Liu et al., 2025; Samadian et al., 2025)		√	Data-driven metamodel approaches in structural engineering (91 studies since 2003), demonstrating accurate prediction with reduced computational cost and identifying key research gaps.
35	(Cheng et al., 2024)		√	Metamodel-based approaches for electric motor design optimization including: statistical, machine learning, deep learning, and AI-based models that enhance optimization efficiency.
36	(L. Liu et al., 2025)		√	Metamodel-assisted multi-objective optimization for electrical machines, covering design of experiments, model construction, and optimization strategies such as transfer learning, multi-fidelity modeling, and search-space reduction.
37	(Misener & Biegler, 2023)		√	Metamodeling approaches for process optimization under uncertainty, including metamodel-led and mathematical programming-led frameworks with applications in heat exchanger network synthesis and drill scheduling.
38	(Ling et al., 2022)		√	Reliability-based design optimization (RBDO) methods with metamodel integration, focusing on reducing computational cost under uncertainty and outlining key advantages, limitations, and research challenges.

4. Strength And Weakness Viewpoints Over RD

The vital role of noise × noise interaction in parameter design problems has been defended by (R. Myers et al., 2016). In addition, the framework of these interactions defines the nature of non-homogeneity of process variance and typifies the design of parameters. The application of robust design optimization has been contributed by a great number of researchers in the quality improvement of various processes or product design in practice, and several appropriate studies have reviewed the application of the Taguchi methodology in real case studies, see (Beyer & Sendhoff, 2007; Dellino et al., 2015; Gabrel et al., 2014; Geletu & Li, 2014; G. J. Park et al., 2006; G. Wang & Shan, 2011).

However, over Taguchi's idea of designing the process with a robust framework, some criticism has been extracted from different studies. (Vining & Myers, 1990) have presented an analytical study on the Taguchi method. They have mentioned five different criticisms of Taguchi's approach to robust parameter design. The first one is the inefficiency of the signal-to-noise ratio. The second one is the shortage of ability in Taguchi design parameters to approach a flexible process modeling. The third one is the number of experiments in Taguchi robust design with their SN ratio that is not economical. Preoccupation with optimization is fourth, and fifth no formal allowance for sequential experimentation. The Taguchi approach with its crossed arrays and signal-to-noise ratios has emphasized the interaction between design variables with each other and has ignored the importance of interaction between design (control) and noise variables (R. Myers et al., 2016).

In addition, some other drawbacks have been connected to the traditional Taguchi approach. First, in designing variables with orthogonal arrays and signal-to-noise ratio, the process constraint is ignored for designing parameters, and second, robust design with the Taguchi approach just deals with a single quality characteristic as a response in each run of the method. So, it could not propose the best design by considering all responses at the same time. Third, the Taguchi method only investigates the best levels of design variables in the discrete region and could not treat whole design ranges (Dellino et al., 2015; G. J. Park et al., 2006).

5. Conclusion

This paper provides an overview of robust design (RD) from Taguchi's perspective, with emphasis on its key tools, including the quality loss function, orthogonal arrays, and crossed array designs. The review further examines recent developments in RD integrated with optimization techniques, classified into model-based and metamodel-based approaches. The analysis reveals a clear trend toward the increasing use of metamodel-based and hybrid optimization methods to handle complex, computationally expensive, and uncertainty-driven engineering problems, particularly in manufacturing systems. Overall, while traditional Taguchi-based methods remain widely used for their simplicity, modern research increasingly focuses on surrogate-assisted and data-driven approaches to improve efficiency and scalability in robust design optimization.

References

Amaran, S., Sahinidis, N. V., Sharda, B., & Bury, S. J. (2016). Simulation optimization: a review of algorithms and applications. *Annals of Operations Research*, *240*(1), 351–380. https://doi.org/10.1007/s10479-015-2019-x

An, Q., Bai, G., Yang, Y., Wang, C., Huang, Q., Liu, C., Chen, S., Cao, J., Zheng, S., Gu, Z., & Xiang, B. (2016). Preparation optimization of ATO particles by robust parameter design. *Materials Science in Semiconductor Processing*, *42*, 354–358. https://doi.org/10.1016/j.mssp.2015.10.023

Ben-Tal, A., Ghaoui, L. El, & Nemirovski, A. (2009). *Robust optimization*. https://doi.org/10.1007/s10957-013-0421-6

Beyer, H. G., & Sendhoff, B. (2007). Robust optimization - A comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, *196*(33), 3190–3218. https://doi.org/10.1016/j.cma.2007.03.003

Celano, G., Faraz, A., & Saniga, E. (2014). Control charts monitoring product's loss to society. *Quality and Reliability Engineering International*, *30*(8), 1393–1407. https://doi.org/10.1002/qre.1562

Cheng, M., Zhao, X., Dhimish, M., Qiu, W., & Niu, S. (2024). A review of data-driven surrogate models for design optimization of electric motors. *IEEE Transactions on Transportation Electrification*, *10*(4), 8413–8431.

Datta, S., & Mahapatra, S. S. (2010). Modeling, simulation and parametric optimization of wire EDM process using response surface methodology coupled with grey-Taguchi technique. *MultiCraft International Journal of Engineering, Science and Technology Extension*, *2*(5), 162–183. https://doi.org/10.4314/ijest.v2i5.60144

Dellino, G., Kleijnen, J. P. C., & Meloni, C. (2010). Robust optimization in simulation: Taguchi and Response Surface Methodology. *International Journal of Production Economics*, *125*(1), 52–59. https://doi.org/10.1016/j.ijpe.2009.12.003

Dellino, G., Kleijnen, Jack, P. C., & Meloni, C. (2015). Metamodel-Based Robust Simulation-Optimization: An Overview. In *In Uncertainty Management in Simulation-Optimization of Complex Systems* (pp. 27–54). Springer US. https://doi.org/10.1007/978-1-4899-7547-8

Erdbrügge, M., Kuhnt, S., & Rudak, N. (2011). Joint optimization of independent multiple responses. *Quality and Reliability Engineering International*, *27*(5), 689–704. https://doi.org/10.1002/qre.1229

Gabrel, V., Murat, C., & Thiele, A. (2014). Recent advances in robust optimization: An overview. *European Journal of Operational Research*, *235*(3), 471–483. https://doi.org/10.1016/j.ejor.2013.09.036

Geletu, A., & Li, P. (2014). Recent Developments in Computational Approaches to Optimization under Uncertainty and Application in Process Systems Engineering. *ChemBioEng Reviews*, *1*(4), 170–190. https://doi.org/10.1002/cben.201400013

Han, M., & Yong Tan, M. H. (2016). Integrated parameter and tolerance design with computer experiments. *IIE Transactions*, *48*(11), 1004–1015. https://doi.org/10.1080/0740817X.2016.1167289

Jin, R., Du, X., & Chen, W. (2003). The use of metamodeling techniques for optimization under uncertainty. In *Structural and Multidisciplinary Optimization* (Vol. 25, Number 2). https://doi.org/10.1007/s00158-002-0277-0

Khan, J., Teli, S. N., & Hada, B. P. (2015). Reduction Of Cost Of Quality By Using Robust Design : A Research Methodology. *International Journal of Mechanical and Industrial Technology*, *2*(2), 122–128.

Kleijnen, J. P. C. (2010). Sensitivity analysis of simulation models: an overview. *Procedia - Social and Behavioral Sciences*, *2*(6), 7585–7586. https://doi.org/10.1016/j.sbspro.2010.05.130

Kleijnen, J. P. C. (2017). Regression and Kriging metamodels with their experimental designs in simulation - a review. *European Journal of Operational Research*, *256*(1), 1–6. https://doi.org/10.1016/j.ejor.2016.06.041

Koehler, J. R., & Owen, A. B. (1996). Chapter 9: Computer experiments. In *Handbook of statistics* (Vol. 13, pp. 261–308). https://doi.org/10.1016/S0169-7161(96)13011-X

Leung, Y. W., & Wang, Y. (2001). An orthogonal genetic algorithm with quantization for global numerical optimization. *IEEE Transactions on Evolutionary Computation*, *5*(1), 41–53. https://doi.org/10.1109/TCST.2011.2171964

Lin, D. K. J., & Tu, W. (1995). Dual response surface optimization. In *Journal of Quality Technology* (Vol. 27, Number 1, pp. 34–39).

Ling, C., Kuo, W., & Xie, M. (2022). An overview of adaptive-surrogate-model-assisted methods for reliability-based design optimization. *IEEE Transactions on Reliability*, *72*(3), 1243–1264.

Liu, L., Li, Z., Kang, H., Xiao, Y., Sun, L., Zhao, H., Zhu, Z. Q., & Ma, Y. (2025). Review of surrogate model assisted multi-objective design optimization of electrical machines: New opportunities and challenges. *Renewable and Sustainable Energy Reviews*, *215*, 115609.

Liu, X., Yue, R.-X., & Chatterjee, K. (2015). Model-robust R-optimal designs in linear regression models. *Journal of Statistical Planning and Inference*, *167*, 135–143. https://doi.org/10.1016/j.jspi.2015.05.003

Misener, R., & Biegler, L. (2023). Formulating data-driven surrogate models for process optimization. *Computers & Chemical Engineering*, *179*, 108411.

Myers, R., C.Montgomery, D., & Anderson-Cook, M, C. (2016). *Response Surface Methodology: Process and Product Optimization Using Designed Experiments-Fourth Edittion*. John Wiley & Sons. https://doi.org/10.1017/CBO9781107415324.004

Myers, R. H., Khuri, A. I., & Vining, G. (1992). Response surface alternatives to the Taguchi robust parameter design approach. *The American Statistician*, *46*(2), 131–139. https://doi.org/10.1080/00031305.1992.10475869

Nha, V. T., Shin, S., & Jeong, S. H. (2013). Lexicographical dynamic goal programming approach to a robust design optimization within the pharmaceutical environment. *European Journal of Operational Research*, *229*(2), 505–517. https://doi.org/10.1016/j.ejor.2013.02.017

Owen, A. B. (1992). Orthogonal arrays for computer experiments, integration and visualization. *Statistica Sinica*, 439–452.

Park, C., & Leeds, M. (2016). A Highly Efficient Robust Design Under Data Contamination. *Computers {&} Industrial Engineering*, *93*, 131–142. https://doi.org/10.1016/j.cie.2015.11.016

Park, G. J., Lee, T. H., Lee, K. H., & Hwang, K. H. (2006). Robust Design : An Overview. *AIAA Journal*, *44*(1), 181–191. https://doi.org/10.2514/1.13639

Park, S. (1996). *Robust design and Analysis for Quality Engineering*. Boom Koninklijke Uitgevers.

Park, S., & Antony, J. (2008). *Robust design for quality engineering and six sigma*. World Scientific Publishing Co Inc.

Parnianifard, A., Azfanizam, A., Ariffin, M., Ismail, M., & Ebrahim, N. (2019). Recent developments in metamodel based robust black-box simulation optimization: An overview. *Decision Science Letters*, *8*(1), 17–44. https://doi.org/10.5267/j.dsl.2018.5.004

Parnianifard, A., & Azfanizam, A. S. (2020). Metamodel‐based robust simulation‐optimization assisted optimal design of multiloop integer and fractional‐order PID controller. *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, *33*(1), e2679. https://doi.org/10.1002/jnm.2679

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2018a). An overview on robust design hybrid metamodeling : Advanced methodology in process optimization under uncertainty. *International Journal of Industrial Engineering Computations*, *9*(1), 1–32. https://doi.org/10.5267/j.ijiec.2017.5.003

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2018b). Design and Analysis of Computer Experiments Using Polynomial Regression and Latin Hypercube Sampling in Optimal Design of PID Controller. *Journal of Applied Research on Industrial Engineering*, *5*(2), 156–168. https://doi.org/10.22105/jarie.2018.141898.1051

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2018c). Kriging-Assisted Robust Black-Box Simulation Optimization in Direct Speed Control of DC Motor Under Uncertainty. *IEEE Transactions on Magnetics*, *54*(7), 1–10. https://doi.org/10.1109/TMAG.2018.2829767

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2019a). Comparative study of metamodeling and sampling design for expensive and semi-expensive simulation models under uncertainty. *SIMULATION*, *96*(1), 89–110. https://doi.org/10.1177/0037549719846988

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2019b). Crossing weighted uncertainty scenarios assisted distribution-free metamodel-based robust simulation optimization. *Engineering with Computers*, *36*(1), 139–150. https://doi.org/10.1007/s00366-018-00690-0

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., & Ismail, M. I. S. (2019c). Trade-off in robustness, cost and performance by a multi-objective robust production optimization method. *International Journal of Industrial Engineering Computations*, *10*(1), 133–148. https://doi.org/10.5267/j.ijiec.2018.2.001

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K., Ismail, M. I., Maghami, M. R., & Gomes, C. (2018). Kriging and Latin Hypercube Sampling Assisted Simulation Optimization in Optimal Design of PID Controller for Speed Control of DC Motor. *Journal of Computational and Theoretical Nanoscience*, *15*(5), 1471–1479. https://doi.org/https://doi.org/10.1166/jctn.2018.7379

Parnianifard, A., Chancharoen, R., Phanomchoeng, G., & Wuttisittikulkij, L. (2020). A New Approach for Low-Dimensional Constrained Engineering Design Optimization Using Design and Analysis of Simulation Experiments. *International Journal of Computational Intelligence Systems*, *13*(1), 1663–1678. https://doi.org/10.2991/ijcis.d.201014.001

Parnianifard, A., Chaudhary, S., Mumtaz, S., Wuttisittikulkij, L., & Imran, M. A. (2023). Expedited surrogate-based quantification of engineering tolerances using a modified polynomial regression. *Structural and Multidisciplinary Optimization*, *66*(3), 61. https://doi.org/10.1007/s00158-023-03493-0

Parnianifard, A., Fakhfakh, M., Kotti, M., Zemouche, A., & Wuttisittikulkij, L. (2020). Robust tuning and sensitivity analysis of stochastic integer and fractional-order PID control systems : application of surrogate-based robust simulation-optimization. *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, *34*(2), e2835. https://doi.org/10.1002/jnm.2835

Parnianifard, A., Mumtaz, S., Chaudhary, S., Imran, M. A., & Wuttisittikulkij, L. (2022). A data driven approach in less expensive robust transmitting coverage and power optimization. *Scientific Reports*, *12*, 17725. https://doi.org/10.1038/s41598-022-21490-z

Parnianifard, A., Pengnoo, M., Imran, M. A., Otaibi, S. Al, Sasithong, P., Vanichchanunt, P., Polysuwan, T., & Wuttisittikulkij, L. (2021a). Hybrid Metamodeling / Metaheuristic Assisted Multi-Transmitters Placement Planning. *Computers, Materials & Continua*, *68*(1), 569–587. https://doi.org/10.32604/cmc.2021.015730

Parnianifard, A., Pengnoo, M., Imran, M. A., Otaibi, S. Al, Sasithong, P., Vanichchanunt, P., Polysuwan, T., & Wuttisittikulkij, L. (2021b). Hybrid Metamodeling / Metaheuristic Assisted Multi-Transmitters Placement Planning. *Computers, Materials & Continua*, *68*(1), 569–587. https://doi.org/10.32604/cmc.2021.015730

Parnianifard, A., Rezaie, V., Chaudhary, S., Imran, M. A., & Wuttisittikulkij, L. (2021). New Adaptive Surrogate-Based Approach Combined Swarm Optimizer Assisted Less Tuning Cost of Dynamic Production- Inventory Control System. *IEEE Access*, *9*, 144054–144066. https://doi.org/10.1109/ACCESS.2021.3122166

Parnianifard, A., Sharma, A., & Chaudhary, S. (2024). A new approach for data-driven surrogate modelling applied in highly nonlinear engineering functions. *Journal of Statistical Computation and Simulation*, 1–24. https://doi.org/10.1080/00949655.2024.2439488

Parnianifard, A., Zemouche, A., Chancharoen, R., Imran, M. A., & Wuttisittikulkij, L. (2020). Robust optimal design of FOPID controller for five bar linkage robot in a Cyber-Physical System: A new simulation-optimization approach. *PLOS ONE*, *15*(11), e0242613. https://doi.org/10.1371/journal.pone.0242613

Parnianifard, A., Zemouche, A., Imran, M. A., & Wuttisittikulkij, L. (2020). Robust simulation-optimization of dynamic-stochastic production/inventory control system under uncertainty using computational intelligence. *Uncertain Supply Chain Management*, *8*(4), 633–648. https://doi.org/10.5267/j.uscm.2020.9.002

Peng, H. P., Jiang, X. Q., Xu, Z. G., & Liu, X. J. (2008). Optimal tolerance design for products with correlated characteristics by considering the present worth of quality loss. *International Journal of Advanced Manufacturing Technology*, *39*(1), 1–8. https://doi.org/10.1007/s00170-007-1205-7

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

Razali, C. M. C., Abdullah, S. S., Parnianifard, A., & Faruq, A. (2020). Adaptive Infill Sampling Strategy for Metamodeling : Challenge and Future Research Directions. *Bulletin of Electrical Engineering and Informatics*, *9*(5), 2020–2029. https://doi.org/10.11591/eei.v9i5.2162

Samadian, D., Muhit, I. B., & Dawood, N. (2025). Application of data-driven surrogate models in structural engineering: a literature review. *Archives of Computational Methods in Engineering*, *32*(2), 735–784.

Sharma, N. K., & Cudney, E. A. (2011). Signal-to-Noise ratio and design complexity based on Unified Loss Function – LTB case with Finite Target. *International Journal of Engineering, Science and Technology*, *3*(7), 15–24.

Sharma, N. K., Cudney, E. A., Ragsdell, K. M., & Paryani, K. (2007). Quality Loss Function – A Common Methodology for Three Cases. *Journal of Industrial and Systems Engineering*, *1*(3), 218–234.

Simpson, T. W., Poplinski, J. D., Koch, P. N., & Allen, J. K. (2001). Metamodels for Computer-based Engineering Design: Survey and recommendations. *Engineering With Computers*, *17*(2), 129–150. https://doi.org/10.1007/PL00007198

Steenackers, G., Guillaume, P., & Vanlanduit, S. (2009). Robust Optimization of an Airplane Component Taking into Account the Uncertainty of the Design Parameters. *Quality and Reliability Engineering International*, *25*(3), 255–282. https://doi.org/10.1002/qre

Tabrizi, B. H., & Ghaderi, S. F. (2016). A robust bi-objective model for concurrent planning of project scheduling and material procurement. *Computers {&} Industrial Engineering*, *98*, 11–29. https://doi.org/10.1016/j.cie.2016.05.017

Tsai, T.-N., & Liukkonen, M. (2016). Robust parameter design for the micro-BGA stencil printing process using a fuzzy logic-based Taguchi method. *Applied Soft Computing*, *48*, 124–136. https://doi.org/10.1016/j.asoc.2016.06.020

Vining, G., & Myers, R. (1990). Response Surface Alternatives to the Taguchi Robust Parameter Design Approach. *Journal of Quality Technology*, *22*(1), 38–45.

Wang, C., Qiang, X., Xu, M., & Wu, T. (2022). Recent Advances in Surrogate Modeling Methods for Uncertainty Quantification and Propagation. In *Symmetry* (Vol. 14, Number 6). MDPI. https://doi.org/10.3390/sym14061219

Wang, G., & Shan, S. (2007). Review of Metamodeling Techniques in Support of Engineering Design Optimization. *Journal of Mechanical Design*, *129*(4), 370–380. https://doi.org/10.1115/1.2429697

Wang, G., & Shan, S. (2011). Review of Metamodeling Techniques for Product Design with Computation-intensive Processes. *Proceedings of the Canadian Engineering Education Association*. https://doi.org/10.1115/1.2429697

Wu, F. (2015). Robust Design of Mixing Static and Dynamic Multiple Quality Characteristics. *World Journal of Engineering and Technology*, *3*(03), 72–77.

Zhang, D., & Lu, Q. (2016). Robust Regression Analysis with LR-Type Fuzzy Input Variables and Fuzzy Output Variable. *Journal of Data Analysis and Information Processing*, *4*(02), 64–80.