INTERVAL OPTIMIZATION APPROACH USING PROGRESSIVE TRIGONOMETRIC MIXED RESPONSE SURFACE METHOD

By

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Chairman : Professor Ir. Mohd Khairol Anuar bin Mohd Ariffin, PhD
Faculty : Engineering

For structural designs, uncertainty is ubiquitous, ranging from simple models to complicated systems, especially in the design of the composite submersible hull. To deal with this problem, a method named uncertain interval optimization was introduced in recent decades. However, the existing interval optimization methods, such as the Nonlinear Interval Number Programming (NINP), which is based on the first-order Taylor expansion, are only suitable for small interval uncertainties. A large range of uncertainties will lead to a significant error. The key challenge becomes how to develop another effective type of interval optimization approach with enough efficient and reliable constraints. Therefore, this research performs a novel double-loop interval optimization approach using the Progressive TMRSM, the reliable constraints, and the MATLAB software to limit the constraints effectively. Nevertheless, double-loop optimization means a high computational cost even if a simulation such as the Finite Element Method (FEM) or experiment is used. To solve this difficulty, a surrogate method is introduced to replace the experiment or the FEM. Recently, there have been various surrogate approaches for structural engineering. Scholars always seek to attain more accurate and simpler models with fewer sample points. Determining how to create a better surrogate model with fewer and more reliable sample points and less other information becomes a critical and urgent topic. This research first updates the traditional Response Surface Method (RSM) to a new proposed Trigonometric Mixed Response Surface Method (TMRSM), which can obtain a more accurate surrogate model with fewer and more reliable sample points. However, the decision of the highest order of the TMRSM should be determined in advance by designers for some high-nonlinear complex structural problems. Another deficiency to be concerned about is how to determine the highest order of polynomials for the RSM surrogate model. Thus, a Progressive Trigonometric Mixed Response Surface Method (Progressive TMRSM) is put forward to determine the highest order for the TMRSM. This Progressive TMRSM consists of the t-test criterion, the determination coefficient,

and the mean relative error. The accuracy and the fitting performance of the TMRSM and the Progressive TMRSM have been verified by four well-known numerical functions. The results show that the Progressive TMRSM has the best accuracy and perfect fitting performance. Due to the complex pressure environment under the water and the uncertainty of the layup technology, the design process of the submersible is faced with several uncertain factors. But the optimization design considering the uncertain factors has not been studied by any scholars. How to apply interval optimization design in the field of submersible designs becomes another significant research issue. So, this research carries out an uncertain interval optimization design (the buckling properties and the failure criterion) for the composite submersible hull based on the interval optimization approach, the Progressive TMRSM, and the Finite Element Method (FEM) method by ANSYS software. This approach can obtain a better solution with a narrower deviation of the objectives compared with NINP.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENDEKATAN PENGOPTIMUMAN SELANG MENGGUNAKAN KAEDAH PERMUKAAN RESPON TRIGONOMETRI PROGRESIF CAMPURAN

Oleh

ZHENG GUANCHAO

Disember 2022

Pengerusi : Profesor Ir. Mohd Khairol Anuar bin Mohd Ariffin, PhD
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Reka bentuk struktur, ketidakpastian ada di mana-mana, bermula daripada model mudah kepada sistem yang rumit, terutamanya dalam reka bentuk badan kapal tenggelam komposit. Untuk menangani masalah ini, kaedah yang dinamakan pengoptimuman selang tidak pasti telah diperkenalkan dalam beberapa dekad kebelakangan ini. Walau bagaimanapun, kaedah pengoptimuman selang sedia ada, seperti Pengaturcaraan Nombor Selang Tak Linear (NINP), yang berdasarkan pengembangan Taylor tertib pertama, hanya sesuai untuk ketidakpastian selang yang kecil. Pelbagai ketidakpastian yang besar akan membawa kepada ralat yang ketara. Cabaran utama ialah bagaimana untuk membangunkan satu lagi jenis pendekatan pengoptimuman selang yang berkesan dengan kekangan yang cekap dan boleh dipercayai. Oleh itu, penyelidikan ini melaksanakan pendekatan pengoptimuman selang dua gelung novel menggunakan TMRSM Progresif, kekangan yang boleh dipercayai, dan perisian MATLAB untuk mengehadkan kekangan dengan berkesan. Namun begitu, pengoptimuman gelung dua kali bermaksud kos pengiraan yang tinggi walaupun simulasi seperti Kaedah Elemen Terhad (FEM) atau eksperimen digunakan. Untuk menyelesaikan kesukaran ini, kaedah pengganti diperkenalkan untuk menggantikan eksperimen atau FEM. Baru-baru ini, terdapat pelbagai pendekatan pengganti untuk kejuruteraan struktur. Sarjana sentiasa berusaha untuk mencapai model yang lebih tepat dan lebih mudah dengan titik sampel yang lebih sedikit. Menentukan cara mencipta model pengganti yang lebih baik dengan titik sampel yang lebih sedikit dan lebih dipercayai serta kurang maklumat lain menjadi topik kritikal dan mendesak. Penyelidikan ini mula-mula mengemas kini Kaedah Permukaan Tindak Balas tradisional (RSM) kepada Kaedah Permukaan Tindak Balas Bercampur Trigonometri (TMRSM) baharu yang dicadangkan, yang boleh mendapatkan model pengganti yang lebih tepat dengan titik sampel yang lebih sedikit dan lebih dipercayai. Walau bagaimanapun, keputusan peringkat tertinggi TMRSM harus ditentukan terlebih dahulu oleh pereka bentuk untuk beberapa masalah

struktur kompleks bukan linear tinggi. Satu lagi kekurangan yang perlu dibimbangkan ialah bagaimana untuk menentukan susunan polinomial tertinggi untuk model pengganti RSM. Oleh itu, Kaedah Permukaan Tindak Balas Campuran Trigonometri Progresif (TMRSM Progresif) dikemukakan untuk menentukan susunan tertinggi bagi TMRSM. TMRSM Progresif ini terdiri daripada kriteria ujian-t, pekali penentuan, dan min ralat relatif. Ketepatan dan prestasi pemasangan TMRSM dan TMRSM Progresif telah disahkan oleh empat fungsi berangka yang terkenal. Keputusan menunjukkan bahawa TMRSM Progresif mempunyai ketepatan yang terbaik dan prestasi pemasangan yang sempurna. Oleh kerana persekitaran tekanan yang kompleks di bawah air dan ketidakpastian teknologi layup, proses reka bentuk tenggelam berhadapan dengan beberapa faktor yang tidak pasti. Tetapi reka bentuk pengoptimuman memandangkan faktor yang tidak pasti belum dikaji oleh mana-mana sarjana. Cara menggunakan reka bentuk pengoptimuman selang dalam bidang reka bentuk tenggelam menjadi satu lagi isu penyelidikan yang penting. Oleh itu, penyelidikan ini menjalankan reka bentuk pengoptimuman selang yang tidak pasti (sifat lengkokan dan kriteria kegagalan) untuk badan kapal selam komposit berdasarkan pendekatan pengoptimuman selang, TMRSM Progresif, dan kaedah Elemen Terhad (FEM) oleh perisian ANSYS. Pendekatan ini boleh mendapatkan penyelesaian yang lebih baik dengan sisihan objektif yang lebih sempit berbanding dengan NINP.

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This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) are adhered to.

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LIST OF ABBREVIATIONS

FEM	Finite Element Method
GA	Genetic Algorithm
ANN	Artificial Neural Network
RSM	Response Surface Method
LHD	Latin Hypercube Design
RBF	Radial Basis Function
MLSM	Moving Least Square Method
NINP	Nonlinear Interval Number Programming
TMRSM	Trigonometric Mixed Response Surface Method
Progressive TMRSM	Progressive Trigonometric Mixed Response Surface Method
OLHD	Optimal Latin Hypercube Design
SQP	Sequential Quadratic Programming,
PSO	Particle Swarm Optimization
SO	Simulation and Optimization
SBO	Surrogate Based Optimization
DoE	Design Of Experiments
FD	Factorial Design
OAD	Orthogonal Arrays Design
CCD	Central Composite Design
ARSM	Adaptive Response Surface Method
BBD	Box-Behnken Design
QR	Quasi-Random
MCS	Monte Carlo Simulation
MARS	Multivariate Adaptive Regression Spline

RBDO	Reliability-Based Design Optimization
MOPSO	Multi-Objective Particle Swarm Optimization
PDF	Probability Density Functions
RDO	Robust Design Optimization
ACP	ANSYS Composite PrepPost
LSM	Least Squares Method
MRE	Mean Relative Error
RMSE	Root Mean Square Error

CHAPTER 1

INTRODUCTION

1.1 Background

Terrestrial resources are becoming increasingly depleted as a result of resource development, while the ocean, as a treasure trove of vast reserves and abundant resources, has exceptionally high research and development values for its mineral, biological, and energy resources. Additionally, as there are some particular demands, such as exploring sunk ships and crashed planes, that is where the underwater submersible becomes important. This submersible technology has a wide range of applications in marine resource exploration, marine environment survey, seabed rescue, and specific search (Zereik et al., 2018).

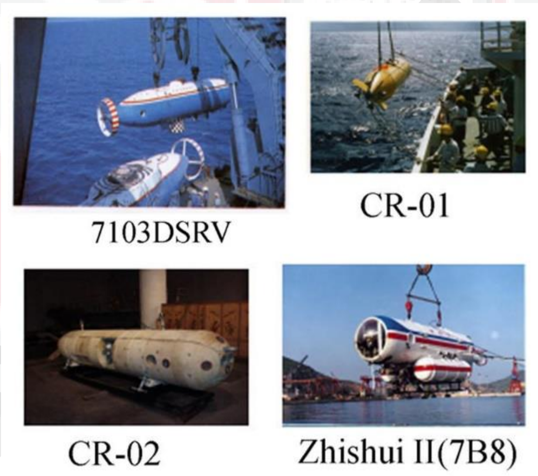

Figure 1.1 : Underwater submersible diagram
(Source : Cui, 2018)

Chinese self-developed 4,500-meter deep-sea submersible "Hai Ma" has been successfully tested in the South China Sea Basin (Walden & Brown, 2004). Japan's submersible, named "Deep Sea 6500" can operate underwater for up to 8 hours (Iwai et al., 1990). Russian "Peace 1" and "Peace 2" can reach a depth of 6,000 meters and can operate for 17-20 hours (Sagalevitch, 1998). The French "Nautilus" submersible can dive 6,000 meters, and it has completed shipwreck and hazardous waste searches, submarine ecological surveys, and other tasks (Boulègue, J., Iiyama, J. T., Charlou, J.-L., & Jedwab, 1987). The US "Alvin" manned submersible has completed 4500 submarine missions (S. Zhang et al., 2019). Therefore, Most of the world's maritime powers have begun to invest heavily in marine detection, and underwater submersible technology has developed rapidly in recent decades (S. Zhang et al., 2019).

Submersibles are becoming deeper dive, longer range, and faster to meet today's increasingly complex functional tasks. These requirements necessitate a submersible with a stronger structure, less weight, less resistance, and greater inner volume. Thus, the submersible hull should be able to carry a higher load in order to meet the strength under extreme pressure in the deep-water environment.

Generally, the most common materials for high-pressure underwater vessels are high-strength steel, aluminum alloy, and titanium alloy (Moon et al., 2010). Ross (2006) also explained that the main materials for submersible pressure hull design are high-strength steels, aluminum alloys, and titanium alloys. A rising application of laminated composite material was recently introduced to improve corrosion resistance and reduce the weight-strength ratio compared with traditional metal material for submersible hulls (Davies et al., 2016; Moon et al., 2010).

Smith (1991) may be the first researcher to propose the use of composite material in the underwater vehicle design field. And immediately after that, the filament winding method was applied to the production of underwater submersibles first time (Hahn HT, Jensen DW, Claus SJ, Pai SP, 1994). With a great number of applications, the filament winding of cylinders focusing on mechanical properties such as buckling, biaxial compression, and failure has become a hot research topic (Davies et al., 2016). Therefore, the use of composite underwater submersible hulls can be considered a promising trend (Upputuri & Nimmagadda, 2020).

1.2 Problem Statement

A lot of scholars have made contributions to the research of composite submersible shells. Messager, Pyrz, Gineste, and Chauchot (2002) described the optimal composite design for the deep submersible based on the Finite Element Method (FEM) and Experiments. Moreover, different orientation angles could affect the buckling feature of the composite shell. Kaneko, Ujihashi, Yomoda, and Inagi (2008) analyzed the impact of the pressurized composite cylinder in different failure conditions for free-from failure based on FEM. Moon et al. (2010) discussed composite cylinder's buckling and failure characteristics under external pressure, which was made by filament winding method using FEM and experiment testing. The results showed that the characteristics were mainly affected by the helical winding angles.

Unfortunately, in practical engineering, hundreds and thousands of optimum calculations for the FEM or Experiments need lots of time, for example, hundreds of hours or a few weeks. In this case, Kemal Apalak, Yildirim, and Ekici (2008) investigated layer optimization with three edge conditions for the maximum fundamental frequency of the composite plate using the Genetic Algorithm (GA) and Artificial Neural Network (ANN) model. This model, named the surrogate model (or the approximate model), was used to replace the FEM or experiment calculations. Mallela and Upadhyay (2016) performed a laminated composite design with the development of a computationally efficient analysis model based on ANN to predict the buckling of the composite shell under in-plane shear loading.

Although these surrogate models provide a reasonable simulation response, more sample points need to be added to provide more precise results. An adaptive Response Surface Method (RSM) was created for high-dimensional design challenges that are based on the Latin Hypercube Design (LHD) by G. Wang (G. G. Wang, 2003). To update the decision function, Basudhar and Missoum (2008) created a precise approximation explicit-decision function based on an adaptive sample method. An adaptive Kriging model was used to improve computation outcomes by adding additional sample points by Cheng et al. (J. Cheng et al., 2014, 2015). Another sequential improvement criterion was performed to obtain the resilient optimization solution while also advancing the appropriateness of the Radial Basis Function (RBF) by Havinga (Havinga et al., 2017). It is important to note that adding more sample points means not only a more accurate response but also a higher processing cost.

Given such deficiencies, many researchers devise and implement more accurate surrogate models with fewer sample points. Kim (2005) and Youn (2004) combined the Moving Least Squares Method (MLSM) and sensitivity information to build a more accurate surrogate model. Li and Kim (2012) presented a doubly-weighted moving least squares approach that incorporates the normal weight factor of MLSM as well as the distance between the most likely failure spots. The RSM was implemented using the MLSM to reduce the computational burden by Kaymaz (2005) and Taflanidis (2012). Even if the aforementioned researchers did their best to construct an accurate surrogate model with a minimal number of sample points, sensitive data or other information is still required. Then Y. Lee and C. Lin proposed a novel RSM with trigonometric functions for composite laminated structures to improve the accuracy of the regression (Y. J. Lee & Lin, 2003; C. C. Lin & Lee, 2004). However, the regression with trigonometric functions only plays a global approximation over the whole domain rather than the local approximation. As a result, determining how to create a better surrogate model with fewer and more reliable sample points and less other information becomes a critical and urgent topic.

It should be noted that all these abovementioned papers construct RSM models by second-order polynomials. Nevertheless, only simple quadratic RSM models may not be sufficient for high-nonlinear engineering problems. In practice, when a high-nonlinear complex structural problem is to be performed, the decision of the highest order of the polynomial should be determined in advance by designers. Hence, another deficiency to be concerned about is how to determine the highest order of polynomials for the RSM surrogate model.

In the traditional design of engineering optimization, deterministic parameters are typically adopted to evaluate structural behavior. However, uncertainty with respect to the actual values for parameters is widespread in practical engineering problems, ranging from simple models to large systems. Geometric dimensions, material qualities, stresses, boundary conditions, manufacturing tolerance, and so forth are examples of intrinsic uncertain elements in real-world situations (F. Li, Luo, Sun, et al., 2013; J. Wu et al., 2013, 2015).

Since the 1960s, Moore and Cloud (2009) proposed an uncertain interval analysis that can calculate the upper bounds and lower bounds of the objective functions without the premise of probabilistic density function or a great number of data. Elishakoff (1994) and Ben-Haim (1994) may start to use this interval analysis for structural engineering to solve uncertain problems. Qiu (1998, 2001) used the anti-optimization technique to solve linear interval equations for small and large interval static displacement bounds of structural performance. A Nonlinear Interval Number Programming (NINP) method is proposed to transform the uncertain optimal situation into a deterministic optimization problem based on penalty functions and the first-order or second-order Taylor expansion method by Jiang (C. Jiang et al., 2014; C. Jiang, Han, Guan, et al., 2007; C. Jiang, Han, Liu, et al., 2008).

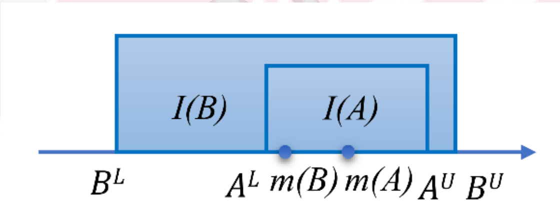

Figure 1.2 : The relationship between two interval values

From the reviews, all these methods are performed with small interval deviations rather than large perturbations. Nonetheless, addressing simply tiny deviation problems in this research is insufficient because most engineering problems are high-nonlinear. For these large interval ranges, Li et al. devised a nested loop optimization approach for engineering design optimization based on Kriging approximate model in order to produce more exact and trustworthy results (F. Li, Luo, Rong, et al., 2013; F. Li, Luo, Sun, et al., 2013). A double-loop optimization was presented using Radial basis functions (RBF) in which the objective and constraints were rebuilt at each iteration step by Zhao (Z. Zhao et al., 2010). Cheng and Liu (2016) constructed a nested genetic algorithm (GA) direct interval ranking procedure with the Kriging model and the degree of Interval Constraint Violation (DICV) to solve the uncertain constraints problems by direct interval relationship. However, this direct interval ranking procedure may lead to an error that the interval A is larger than the interval B when $m(A) > m(B)$ (See Figure 1.2).

In order to treat the constraints for interval optimization, a penalty function is introduced by J. Cheng, C. Jiang and F. Li (J. Cheng et al., 2013; C. Jiang, Han, & Liu, 2007, 2008b; F. Li, Luo, Rong, et al., 2013; F. Li, Luo, Sun, et al., 2013). However, the use of the penalty function may not limit the constraints strictly. In conclusion, the key challenge becomes how to develop another effective type of interval optimization approach with enough efficient and reliable constraints.

For the practical application, none of the scholars put their focus on the interval optimization design for the mechanical performance of the underwater submersible hull. Thus, how to apply uncertain interval optimization design in the field of submersible designs becomes another significant research issue. At last, the problem statements can be summarized as:

1. Determining how to create a better surrogate model with fewer and more reliable sample points and less other information becomes a critical and urgent topic.
2. Another deficiency to be concerned about is how to determine the highest order of polynomials for the RSM surrogate model.
3. The key challenge becomes how to develop another effective type of interval optimization approach with enough efficient and reliable constraints.
4. How to apply uncertain interval optimization design in the field of submersible designs becomes another significant research issue.

1.3 Research Objectives

This research aims to design a new interval optimization process for composite submersible hull applications based on the interval Progressive TMRSM. In order to fulfill this target, there are several objectives that need to be met below:

1. Update the traditional Response Surface Method (RSM) to a new proposed Trigonometric Mixed Response Surface Method (TMRSM), which can obtain a more accurate surrogate model with fewer and more reliable sample points.
2. Develop a Progressive TMRSM model, which can determine the highest order terms of the TMRSM as a surrogate model in the uncertain optimization.
3. Perform a novel double-loop interval optimization approach using the Progressive TMRSM, the reliable constraints, and the MATLAB software to limit the constraints effectively.

4. Carry out the optimization design (the buckling properties and the failure criterion) for the composite submersible hull based on the interval optimization approach, the Progressive TMRSM, and the Finite Element Method (FEM) method by ANSYS software.

1.4 Research Contributions

This research aims to solve an uncertain optimization structural problem based on a novel proposed Progressive TMRSM model and the interval optimization approach for submersible composite hulls. And this novel interval Progressive TMRSM model can iteratively ensure the highest order of the polynomial terms and obtain a more accurate model with fewer samples and less information. Then a double-loop interval optimization approach is performed to reduce the overestimation problem and save computational costs. The detailed contributions of this research are listed as follows:

1. A novel approximate method named the Trigonometric Mixed Response Surface Method (TMRSM) is proposed based on the Optimal Latin Hypercube Design (OLHD), the Moving Least Square Method (MLSM), and trigonometric functions. And this method will be proven to be more accurate than traditional RSM using MATLAB software.
2. A Progressive TMRSM is firstly put forward to decide the highest order of the polynomial based on the t-statistic test, the determination coefficient, and the mean relative error.
3. A new proposed interval optimization approach is presented to obtain enough efficient and reliable constraints.
4. The optimal process for the composite submersible hull is designed considering the orientation angles as variables and the layer thicknesses and underwater pressures as uncertain interval parameters.

1.5 Scope and Limitations

Throughout this research, the design of the composite submersible hull is only focused on the optimization design of the buckling performance and the failure criterion. Other optimal design properties, such as resistance, controllability, or vibration performance, are out of the scope of this research. Furthermore, the simulation of the critical buckling pressure and the Tsai-Wu failure criterion factor index is carried out by the ANSYS simulation rather than the actual experiment.

In addition, the proposed interval optimization approach in this research is just one type of uncertain optimization in which the uncertain parameters are random in the interval bounds. Other uncertain optimization methods, such as probabilistic and fuzzy optimization, are not included in this work. Moreover, the optimization algorithm utilizes mature algorithms (Sequential Quadratic Programming, SQP, and Particle Swarm Optimization, PSO). Some recent algorithms, such as the Whale Optimization Algorithm (WOA), the Grey Wolf Optimizer (GWO), Salp Swarm Algorithm (SSA), and the Bald Eagle Search Optimization Algorithm (BES), are also out of the scope of this study.

For the surrogate approaches, both the proposed TMRSM and the Progressive TMRSM are the basis of the RSM, which may have a strong advantage over continuous functions. And these two models are suitable for problems with orientation angles. Nevertheless, ANN algorithms with wider practicability are beyond the scope of this research.

1.6 Thesis Outline

This research is organized by the layout style 2 of the Guide to Thesis Preparation, School of Graduate Studies, Universiti Putra Malaysia. This research will be arranged into six chapters. The overview description of this research is shown in Figure 1.3. The rest of the research can be listed as:

Chapter 2: This chapter is to introduce the development of the literature review on the subject of this research. The review of the literature includes the sampling method, approximate method, and uncertain optimization method.

Chapter 3: In this chapter, the simulation of the EFM can be expressed to work out the mechanical properties of the composite submersible hull. In this simulation, the buckling and the Tsai-Wu failure criterion of the composite submersible hull can be performed as the mechanical properties. Then a process of the OLHD samples can be established and settled based on ANSYS and Isight software.

Chapter 4: A novel Trigonometric Mixed Response Surface Method (TMRSM) is proposed based on the OLHD, the MLSM, and the trigonometric functions using MATLAB software. Then a method that can determine the highest order of the polynomial named Progressive TMRSM can be put forward based on the t-statistic test, the determination coefficient, and the mean relative error.

Chapter 5: This chapter establishes an interval optimization approach for the composite submersible hull design associated with the interval Progressive TMRSM model using MATLAB software. The design results and the analysis can be carried out in this part.

Chapter 6: The conclusion of this research can be made in this chapter. And the significant points of this study are highlighted. Furthermore, suggestions for future research are also proposed to guide the direction of further research.

1.7 Summary

This chapter introduces the background of this research. Then, the problem statements are proposed, following the background and research status. Furthermore, four research objectives and four research contributions are described based on the problem statements. After that, each research plan is listed in six chapters, including overview descriptions.

REFERENCES

Abdulelah Al-Sudani, Z., Salih, S. Q., sharafati, A., & Yaseen, Z. M. (2019a). Development of multivariate adaptive regression spline integrated with differential evolution model for streamflow simulation. *Journal of Hydrology*, *573*(March), 1–12. https://doi.org/10.1016/j.jhydrol.2019.03.004

Abdulelah Al-Sudani, Z., Salih, S. Q., sharafati, A., & Yaseen, Z. M. (2019b). Development of multivariate adaptive regression spline integrated with differential evolution model for streamflow simulation. *Journal of Hydrology*, *573*(February), 1–12. https://doi.org/10.1016/j.jhydrol.2019.03.004

Abdulredha, M. M., Hussain, S. A., & Abdullah, L. C. (2020). Optimization of the demulsification of water in oil emulsion via non-ionic surfactant by the response surface methods. *Journal of Petroleum Science and Engineering*, *184*(September 2019), 106463. https://doi.org/10.1016/j.petrol.2019.106463

Abouhamze, M., & Shakeri, M. (2007). Multi-objective stacking sequence optimization of laminated cylindrical panels using a genetic algorithm and neural networks. *Composite Structures*, *81*(2), 253–263. https://doi.org/10.1016/j.compstruct.2006.08.015

Abueidda, D. W., Almasri, M., Ammourah, R., Ravaioli, U., Jasiuk, I. M., & Sobh, N. A. (2019). Prediction and optimization of mechanical properties of composites using convolutional neural networks. *Composite Structures*, *227*(April), 111264. https://doi.org/10.1016/j.compstruct.2019.111264

Abyani, M., & Bahaari, M. R. (2020). A comparative reliability study of corroded pipelines based on Monte Carlo Simulation and Latin Hypercube Sampling methods. *International Journal of Pressure Vessels and Piping*, *181*(February), 104079. https://doi.org/10.1016/j.ijpvp.2020.104079

Adali, S., Lene, F., Duvaut, G., & Chiaruttini, V. (2003). Optimization of laminated composites subject to uncertain buckling loads. *Composite Structures*, *62*(3–4), 261–269. https://doi.org/10.1016/j.compstruct.2003.09.024

Adali, S., Summers, E. B., & Verijenko, V. E. (1993). Optimisation of laminated cylindrical pressure vessels under strength criterion. *Composite Structures*, *25*(1–4), 305–312. https://doi.org/10.1016/0263-8223(93)90177-R

Allaix, D. L., & Carbone, V. I. (2011). An improvement of the response surface method. *Structural Safety*, *33*(2), 165–172. https://doi.org/10.1016/j.strusafe.2011.02.001

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

Amin, J. S., Souraki, B. A., Ghavami, M., & Tondro, H. (2011). Prediction of equilibrium water loss during osmotic dehydration in green bean using artificial neural network. *7th International Chemical Engineering Congress & Exihibition*, 21–24.

Ammeri, A;Hachicha, W.;Chabchoub, H.& Masmoudi, F. (2011). A COMPREHENSIVE LITTERATURE REVIEW OF MONO-OBJECTIVE SIMULATION OPTIMIZATION METHODS. *Advances in Production Engineering & Management*, *6*(4), 291–302.

Annoni, P., Bruggemann, R., & Saltelli, A. (2012). Random and quasi-random designs in variance-based sensitivity analysis for partially ordered sets. *Reliability Engineering and System Safety*, *107*, 184–189. https://doi.org/10.1016/j.ress.2012.05.001

Asadzadeh, S., & Khoshbayan, S. (2018). Multi-objective optimization of influential factors on production process of foamed concrete using Box-Behnken approach. *Construction and Building Materials*, *170*, 101–110. https://doi.org/10.1016/j.conbuildmat.2018.02.189

B., L. Fox, I., & PARKE. (1968). Chebyshev polynomials in numerical analysis. *Oxford University Press*, *205*(42s).

Bahloul, R., Arfa, H., & Belhadjsalah, H. (2014). A study on optimal design of process parameters in single point incremental forming of sheet metal by combining Box-Behnken design of experiments, response surface methods and genetic algorithms. *International Journal of Advanced Manufacturing Technology*, *74*(1–4), 163–185. https://doi.org/10.1007/s00170-014-5975-4

Basudhar, A., & Missoum, S. (2008). Adaptive explicit decision functions for probabilistic design and optimization using support vector machines. *Computers and Structures*, *86*(19–20), 1904–1917. https://doi.org/10.1016/j.compstruc.2008.02.008

Ben-Haim, Y. (1994). Convex models of uncertainty: applications and implications. *Erkenntnis*, *41*(2), 139–156.

Bhosekar, A., & Ierapetritou, M. (2018). Advances in surrogate based modeling, feasibility analysis, and optimization: A review. *Computers and Chemical Engineering*, *108*, 250–267. https://doi.org/10.1016/j.compchemeng.2017.09.017

Bogoclu, C., Roos, D., & Nestorović, T. (2021). Local Latin hypercube refinement for multi-objective design uncertainty optimization. *Applied Soft Computing*, *112*, 107807. https://doi.org/10.1016/j.asoc.2021.107807

Bose, R. C., & Bush, K. A. (1952). Orthogonal arrays of strength two and three. *The Annals of Mathematical Statistics*, 508–524.

Boulègue, J., Iiyama, J. T., Charlou, J.-L., & Jedwab, J. (1987). *Nankai Trough , Japan Trench and Kuril Trench : geochemistry of Fluids sampled by submersible " Nautile "*. *83*, 363–375.

Box, G. E.P., & Behnken, D. W. (1960). Some New Three Level Designs for the Study of Quantitative Variables. *Technometrics*, *2*(4), 455–475. https://doi.org/10.1080/00401706.1960.10489912

Box, George E P, & Hunter, J. S. (1957). Multi-factor experimental designs for exploring response surfaces. *The Annals of Mathematical Statistics*, *28*(1), 195–241.

Caflisch, R. E., Morokoff, W. J., & Owen, A. B. (1997). *Valuation of mortgage backed securities using Brownian bridges to reduce effective dimension* (Vol. 24). Department of Mathematics, University of California, Los Angeles.

Cawley, G. C., & Talbot, N. L. C. (2008). Efficient approximate leave-one-out cross-validation for kernel logistic regression. *Machine Learning*, *71*(2–3), 243–264. https://doi.org/10.1007/s10994-008-5055-9

Chen, R. B., Hsieh, D. N., Hung, Y., & Wang, W. (2013). Optimizing Latin hypercube designs by particle swarm. *Statistics and Computing*, *23*(5), 663–676. https://doi.org/10.1007/s11222-012-9363-3

Chen, S. H., & Wu, J. (2004). Interval optimization of dynamic response for uncertain structures with natural frequency constraints. *Engineering Structures*, *26*(2), 221–232. https://doi.org/10.1016/j.engstruct.2003.09.012

Chen, S., Lian, H., & Yang, X. (2002). Interval static displacement analysis for structures with interval parameters. *International Journal for Numerical Methods in Engineering*, *53*(2), 393–407. https://doi.org/10.1002/nme.281

CHENG, C.-S. (1980). Orthogonal arrays with variable numbers of symbols. *The Annals of Statistics*, *8*(2), 447–453.

Cheng, H., Garrick, D. J., & Fernando, R. L. (2017). Efficient strategies for leave-one-out cross validation for genomic best linear unbiased prediction. *Journal of Animal Science and Biotechnology*, *8*(1), 1–5. https://doi.org/10.1186/s40104-017-0164-6

Cheng, J., Duan, G. F., Liu, Z. Y., Li, X. G., Feng, Y. X., & Chen, X. H. (2014). Interval multiobjective optimization of structures based on radial basis function, interval analysis, and NSGA-II. *Journal of Zhejiang University: Science A*, *15*(10), 774–788. https://doi.org/10.1631/jzus.A1300311

Cheng, J., Liu, Z., & Tan, J. (2013). Multiobjective optimization of injection molding parameters based on soft computing and variable complexity method. *International Journal of Advanced Manufacturing Technology*, *66*(5–8), 907–916. https://doi.org/10.1007/s00170-012-4376-9

Cheng, J., Liu, Z., Wu, Z., Li, X., & Tan, J. (2015). Robust optimization of structural dynamic characteristics based on adaptive Kriging model and CNSGA. *Structural and Multidisciplinary Optimization*, *51*(2), 423–437. https://doi.org/10.1007/s00158-014-1140-9

Cheng, J., Liu, Z., Wu, Z., Tang, M., & Tan, J. (2016). Direct optimization of uncertain structures based on degree of interval constraint violation. *Computers and Structures*, *164*, 83–94. https://doi.org/10.1016/j.compstruc.2015.11.006

Chi, H. W., & Bloebaum, C. L. (1995). Mixed variable optimization using Taguchi's orthogonal arrays. *Proceedings of the ASME Design Engineering Technical Conference*, *1*(27), 501–508. https://doi.org/10.1115/DETC1995-0066

Cho, I., Lee, Y., Ryu, D., & Choi, D. H. (2017). Comparison study of sampling methods for computer experiments using various performance measures. *Structural and Multidisciplinary Optimization*, *55*(1), 221–235. https://doi.org/10.1007/s00158-016-1490-6

Choudhury, I. A., & El-Baradie, M. A. (1997). Surface roughness prediction in the turning of high-strength steel by factorial design of experiments. *Journal of Materials Processing Technology*, *67*(1–3), 55–61. https://doi.org/10.1016/S0924-0136(96)02818-X

Cressie, N. (1988). Spatial prediction and ordinary kriging. *Mathematical Geology*, *20*(4), 405–421. https://doi.org/10.1007/BF00892986

Cui, W. (2018). An Overview of Submersible Research and Development in China. *Journal of Marine Science and Application*, *17*(4), 459–470. https://doi.org/10.1007/s11804-018-00062-6

Dantzig, G. (1955). LINEAR PROGRAMMING UNDER UNCERTAINTY. *Management Science*, *Volume 1*, numbers 3, 4.

Davies, P., Choqueuse, D., Bigourdan, B., & Chauchot, P. (2016). Composite Cylinders for Deep Sea Applications: An Overview. *Journal of Pressure Vessel Technology, Transactions of the ASME*, *138*(6), 1–8. https://doi.org/10.1115/1.4033942

de Leon-Delgado, H., Praga-Alejo, R. J., Gonzalez-Gonzalez, D. S., & Cantú-Sifuentes, M. (2018). Multivariate statistical inference in a radial basis function neural network. *Expert Systems with Applications*, *93*, 313–321. https://doi.org/10.1016/j.eswa.2017.10.024

Do, B., Ohsaki, M., & Yamakawa, M. (2021). Bayesian optimization for robust design of steel frames with joint and individual probabilistic constraints. *Engineering Structures*, *245*(January), 112859. https://doi.org/10.1016/j.engstruct.2021.112859

Dong, M., & Wang, N. (2011). Adaptive network-based fuzzy inference system with leave-one-out cross-validation approach for prediction of surface roughness. *Applied Mathematical Modelling*, *35*(3), 1024–1035. https://doi.org/10.1016/j.apm.2010.07.048

Ebrahimi, M., Azimi, E., Nasiri, M., & Azimi, Y. (2021). Hybrid PSO enhanced ANN model and central composite design for modelling and optimization of Low-Intensity magnetic separation of hematite. *Minerals Engineering*, *170*(May), 106987. https://doi.org/10.1016/j.mineng.2021.106987

Elishakoff, I., Cai, G. Q., & Starnes, J. H. (1994). Non-linear buckling of a column with initial imperfection via stochastic and non-stochastic convex models. *International Journal of Non-Linear Mechanics*, *29*(1), 71–82. https://doi.org/10.1016/0020-7462(94)90053-1

Elishakoff, I., Haftka, R. T., & Fang, J. (1994). Structural design under bounded uncertainty-Optimization with anti-optimization. *Computers and Structures*, *53*(6), 1401–1405. https://doi.org/10.1016/0045-7949(94)90405-7

Elishakoff, I., & Thakkar, K. (2014). Overcoming overestimation characteristic to classical interval analysis. *AIAA Journal*, *52*(9), 2093–2097. https://doi.org/10.2514/1.J053152

Elishakoff, Isaac, & Miglis, Y. (2012a). Novel parameterized intervals may lead to sharp bounds. *Mechanics Research Communications*, *44*, 1–8. https://doi.org/10.1016/j.mechrescom.2012.04.004

Elishakoff, Isaac, & Miglis, Y. (2012b). Overestimation-free computational version of interval analysis. *International Journal for Computational Methods in Engineering Science and Mechanics*, *13*(5), 319–328. https://doi.org/10.1080/15502287.2012.683134

Erdös, P., & Kac, M. (1947). On the number of positive sums of independent random variables. *Bulletin of the American Mathematical Society*, *53*(10), 1011–1020.

Fang, H., Rais-Rohani, M., Liu, Z., & Horstemeyer, M. F. (2005). A comparative study of metamodeling methods for multiobjective crashworthiness optimization. *Computers and Structures*, *83*(25–26), 2121–2136. https://doi.org/10.1016/j.compstruc.2005.02.025

Fang, Hongbing, & Horstemeyer, M. F. (2006). Global response approximation with radial basis functions. *Engineering Optimization*, *38*(4), 407–424. https://doi.org/10.1080/03052150500422294

Fathallah, E., Qi, H., Tong, L., & Helal, M. (2014). Design optimization of composite elliptical deep-submersible pressure hull for minimizing the buoyancy factor. *Advances in Mechanical Engineering*, *2014*. https://doi.org/10.1155/2014/987903

Fathallah, E., Qi, H., Tong, L., & Helal, M. (2015). Design optimization of lay-up and composite material system to achieve minimum buoyancy factor for composite elliptical submersible pressure hull. *Composite Structures*, *121*, 16–26. https://doi.org/10.1016/j.compstruct.2014.11.002

Ferrari, R., Froio, D., Rizzi, E., Gentile, C., & Chatzi, E. N. (2019). Model updating of a historic concrete bridge by sensitivity- and global optimization-based Latin Hypercube Sampling. *Engineering Structures*, *179*(December 2017), 139–160. https://doi.org/10.1016/j.engstruct.2018.08.004

Figueira, G., & Almada-Lobo, B. (2014). Hybrid simulation-optimization methods: A taxonomy and discussion. *Simulation Modelling Practice and Theory*, *46*, 118–134. https://doi.org/10.1016/j.simpat.2014.03.007

Friedman, J. H. (1991). Multivariate Adaptive Regressive Splines. *Stanford University*, *19*(1), 1–67.

Fu, Chao, Zhu, W., Yang, Y., Zhao, S., & Lu, K. (2022). Surrogate modeling for dynamic analysis of an uncertain notched rotor system and roles of Chebyshev parameters. *Journal of Sound and Vibration*, *524*(December 2021), 116755. https://doi.org/10.1016/j.jsv.2022.116755

Fu, Chunming, & Cao, L. (2019). An uncertain optimization method based on interval differential evolution and adaptive subinterval decomposition analysis. *Advances in Engineering Software*, *134*(April), 1–9. https://doi.org/10.1016/j.advengsoft.2019.05.001

Fu, Chunming, Liu, Y., & Xiao, Z. (2019). Interval differential evolution with dimension-reduction interval analysis method for uncertain optimization problems. *Applied Mathematical Modelling*, *69*, 441–452. https://doi.org/10.1016/j.apm.2018.12.025

Fu, H. Y., Xu, P. C., Huang, G. H., Chai, T., Hou, M., & Gao, P. F. (2012). Effects of aeration parameters on effluent quality and membrane fouling in a submerged membrane bioreactor using Box-Behnken response surface methodology. *Desalination*, *302*, 33–42. https://doi.org/10.1016/j.desal.2012.06.018

Gavin, H. P., & Yau, S. C. (2008). High-order limit state functions in the response surface method for structural reliability analysis. *Structural Safety*, *30*(2), 162–179. https://doi.org/10.1016/j.strusafe.2006.10.003

Ghodousian, A., & Parvari, M. R. (2017). A modified PSO algorithm for linear optimization problem subject to the generalized fuzzy relational inequalities with fuzzy constraints (FRI-FC). *Information Sciences*, *418–419*, 317–345. https://doi.org/10.1016/j.ins.2017.07.032

Gliszczyński, A., & Kubiak, T. (2017). Load-carrying capacity of thin-walled composite beams subjected to pure bending. *Thin-Walled Structures*, *115*(October 2016), 76–85. https://doi.org/10.1016/j.tws.2017.02.009

Goswami, S., Ghosh, S., & Chakraborty, S. (2016). Reliability analysis of structures by iterative improved response surface method. *Structural Safety*, *60*, 56–66. https://doi.org/10.1016/j.strusafe.2016.02.002

Gunst, R. F., Myers, H., & Montgomery, D. C. (1996). Response Surface Methodology: Process and Product Optimization Using Designed Experiments. In *Technometrics*.

Guo, J. yuan, Lu, W. xi, Yang, Q. chun, & Miao, T. sheng. (2019). The application of 0–1 mixed integer nonlinear programming optimization model based on a surrogate model to identify the groundwater pollution source. *Journal of Contaminant Hydrology*, *220*(November 2018), 18–25. https://doi.org/10.1016/j.jconhyd.2018.11.005

Hahn HT, Jensen DW, Claus SJ, Pai SP, H. P. (1994). *Structural design criteria for filament-wound composite shells*. NASA CR195125.

Handscomb, D. C. (2003). Chevyshev POLYNOMIALS. In *New York*.

Hang, Y., Qu, M., & Ukkusuri, S. (2011). Optimizing the design of a solar cooling system using central composite design techniques. *Energy & Buildings*, *43*(4), 988–994. https://doi.org/10.1016/j.enbuild.2010.12.024

Hassan, M., Najaran, T., Reza, M., & Tootounchi, A. (2020). Probabilistic optimization algorithms for real-coded problems and its application in Latin hypercube problem. *Expert Systems With Applications*, *160*, 113589. https://doi.org/10.1016/j.eswa.2020.113589

Havinga, J., van den Boogaard, A. H., & Klaseboer, G. (2017). Sequential improvement for robust optimization using an uncertainty measure for radial basis functions. *Structural and Multidisciplinary Optimization*, *55*(4), 1345–1363. https://doi.org/10.1007/s00158-016-1572-5

Helton, J. C., & Davis, F. J. (2003). Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering and System Safety*, *81*(1), 23–69. https://doi.org/10.1016/S0951-8320(03)00058-9

Hong, L. J., Bay, C. W., Kong, H., & Nelson, B. L. (2009). *A BRIEF INTRODUCTION TO OPTIMIZATION VIA SIMULATION*. *2002*, 75–85.

Hou, S., Dong, D., Ren, L., & Han, X. (2012). Multivariable crashworthiness optimization of vehicle body by unreplicated saturated factorial design. *Structural and Multidisciplinary Optimization*, *46*(6), 891–905. https://doi.org/10.1007/s00158-012-0799-z

Hou, S., Liu, T., Dong, D., & Han, X. (2014). Factor screening and multivariable crashworthiness optimization for vehicle side impact by factorial design. *Structural and Multidisciplinary Optimization*, *49*(1), 147–167. https://doi.org/10.1007/s00158-013-0957-y

Hu, Z., Bicker, R., & Marshall, C. (2007). Prediction of depth removal in leather surface grit blasting using neural networks and Box-Behnken design of experiments. *International Journal of Advanced Manufacturing Technology*, *32*(7–8), 732–738. https://doi.org/10.1007/s00170-005-0381-6

Huang, D., Allen, T. T., Notz, W. I., & Zeng, N. (2006). Global optimization of stochastic black-box systems via sequential kriging meta-models. *Journal of Global Optimization*, *34*(3), 441–466. https://doi.org/10.1007/s10898-005-2454-3

Huang, Z., Wang, C., Chen, J., & Tian, H. (2011). Optimal design of aeroengine turbine disc based on kriging surrogate models. *Computers and Structures*, *89*(1–2), 27–37. https://doi.org/10.1016/j.compstruc.2010.07.010

Iwai, Y., Nakanishi, T., & Takauasii, K. (1990). *SEA TRIALS AND SUPPORTING TECHNOLOGIES OF MANNED SUBMERSIBLE " SHINKAI 6500 "*. *December*.

Javidrad, F., Nazari, M., & Javidrad, H. R. (2018). Optimum stacking sequence design of laminates using a hybrid PSO-SA method. *Composite Structures*, *185*(May 2017), 607–618. https://doi.org/10.1016/j.compstruct.2017.11.074

Jiang, C., Han, X., Guan, F. J., & Li, Y. H. (2007). An uncertain structural optimization method based on nonlinear interval number programming and interval analysis method. *Engineering Structures*, *29*(11), 3168–3177. https://doi.org/10.1016/j.engstruct.2007.01.020

Jiang, C., Han, X., & Liu, G. P. (2008a). A sequential nonlinear interval number programming method for uncertain structures. *Computer Methods in Applied Mechanics and Engineering*, *197*(49–50), 4250–4265. https://doi.org/10.1016/j.cma.2008.04.027

Jiang, C., Han, X., & Liu, G. P. (2008b). Uncertain optimization of composite laminated plates using a nonlinear interval number programming method. *Computers and Structures*, *86*(17–18), 1696–1703. https://doi.org/10.1016/j.compstruc.2008.02.009

Jiang, C., Han, X., & Liu, G. R. (2007). Optimization of structures with uncertain constraints based on convex model and satisfaction degree of interval. *Computer Methods in Applied Mechanics and Engineering*, *196*(49–52), 4791–4800. https://doi.org/10.1016/j.cma.2007.03.024

Jiang, C., Han, X., Liu, G. R., & Liu, G. P. (2008). A nonlinear interval number programming method for uncertain optimization problems. *European Journal of Operational Research*, *188*(1), 1–13. https://doi.org/10.1016/j.ejor.2007.03.031

Jiang, C., Zhang, Z. G., Zhang, Q. F., Han, X., Xie, H. C., & Liu, J. (2014). A new nonlinear interval programming method for uncertain problems with dependent interval variables. *European Journal of Operational Research*, *238*(1), 245–253. https://doi.org/10.1016/j.ejor.2014.03.029

Jiang, Chao, Fu, C. M., Ni, B. Y., & Han, X. (2016). Interval arithmetic operations for uncertainty analysis with correlated interval variables. *Acta Mechanica Sinica/Lixue Xuebao*, *32*(4), 743–752. https://doi.org/10.1007/s10409-015-0525-3

Jin, R., Chen, W., & Simpson, T. W. (2001). Comparative studies of metamodelling techniques under multiple modelling criteria. *Structural and Multidisciplinary Optimization*, *23*(1), 1–13. https://doi.org/10.1007/s00158-001-0160-4

Kaneko, T., Ujihashi, S., Yomoda, H., & Inagi, S. (2008). Finite element method failure analysis of a pressurized FRP cylinder under transverse impact loading. *Thin-Walled Structures*, *46*(7–9), 898–904. https://doi.org/10.1016/j.tws.2008.01.016

Kang, F., Han, S., Salgado, R., & Li, J. (2015). System probabilistic stability analysis of soil slopes using Gaussian process regression with Latin hypercube sampling. *Computers and Geotechnics*, *63*, 13–25. https://doi.org/10.1016/j.compgeo.2014.08.010

Kar, D., Ghosh, M., Guha, R., Sarkar, R., Garcia-Hernandez, L., & Abraham, A. (2020). Fuzzy mutation embedded hybrids of gravitational search and Particle Swarm Optimization methods for engineering design problems. *Engineering Applications of Artificial Intelligence*, *95*(July), 103847. https://doi.org/10.1016/j.engappai.2020.103847

Kaymaz, I., & McMahon, C. A. (2005). A response surface method based on weighted regression for structural reliability analysis. *Probabilistic Engineering Mechanics*, *20*(1), 11–17. https://doi.org/10.1016/j.probengmech.2004.05.005

Kearns, M., & Ron, D. (1997). Algorithmic stability and sanity-check bounds for leave-one-out cross-validation. *Proceedings of the Annual ACM Conference on Computational Learning Theory*, 152–162. https://doi.org/10.1145/267460.267491

Keivanian, F., & Chiong, R. (2022). A novel hybrid fuzzy–metaheuristic approach for multimodal single and multi-objective optimization problems. *Expert Systems with Applications*, *195*(November 2021), 116199. https://doi.org/10.1016/j.eswa.2021.116199

Kelesoglu, O. (2007). Fuzzy multiobjective optimization of truss-structures using genetic algorithm. *Advances in Engineering Software*, *38*(10), 717–721. https://doi.org/10.1016/j.advengsoft.2007.03.003

Kemal Apalak, M., Yildirim, M., & Ekici, R. (2008). Layer optimisation for maximum fundamental frequency of laminated composite plates for different edge conditions. *Composites Science and Technology*, *68*(2), 537–550. https://doi.org/10.1016/j.compscitech.2007.06.031

Keskin, I., Dag, B., Sariyel, V., & Gokmen, M. (2009). Estimation of growth curve parameters in Konya Merino sheep. *South African Journal of Animal Sciences*, *39*(2), 163–168.

Kim, C., Wang, S., & Choi, K. K. (2005). Efficient response surface modeling by using moving least-squares method and sensitivity. *AIAA Journal*, *43*(11), 2404–2411. https://doi.org/10.2514/1.12366

Kim, T. U., & Sin, H. C. (2001). Optimal design of composite laminated plates with the discreteness in ply angles and uncertainty in material properties considered. *Computers and Structures*, *79*(29–30), 2501–2509. https://doi.org/10.1016/S0045-7949(01)00133-X

Kolakowski, Z. (2003). On some aspects of the modified TSAI-WU criterion in thin-walled composite structures. *Thin-Walled Structures*, *41*(4), 357–374. https://doi.org/10.1016/S0263-8231(02)00112-X

Kollar, L. P., & Springer, G. S. (2003). *Mechanics of composite Structures*. Cambridge university press.

Krige, D. G. (1951). A Statistical Approach to Some Basic Mine Valuation Problems on the Witwatersrand. *Doctoral Dissertation, University of the Witwatersrand*. https://doi.org/10.2307/3006914

Lan, Z., & Gong, B. (2020). Uncertainty analysis of key factors affecting fracture height based on box-behnken method. *Engineering Fracture Mechanics*, *228*(September 2019), 106902. https://doi.org/10.1016/j.engfracmech.2020.106902

Lee, G. C., Kweon, J. H., & Choi, J. H. (2013). Optimization of composite sandwich cylinders for underwater vehicle application. *Composite Structures*, *96*, 691–697. https://doi.org/10.1016/j.compstruct.2012.08.055

Lee, T. S., & Chen, I. F. (2005). A two-stage hybrid credit scoring model using artificial neural networks and multivariate adaptive regression splines. *Expert Systems with Applications*, *28*(4), 743–752. https://doi.org/10.1016/j.eswa.2004.12.031

Lee, T. S., Chiu, C. C., Chou, Y. C., & Lu, C. J. (2006). Mining the customer credit using classification and regression tree and multivariate adaptive regression splines. *Computational Statistics and Data Analysis*, *50*(4), 1113–1130. https://doi.org/10.1016/j.csda.2004.11.006

Lee, Y. J., & Lin, C. C. (2003). Regression of the response surface of laminated composite structures. *Composite Structures*, *62*(1), 91–105. https://doi.org/10.1016/S0263-8223(03)00095-3

Lefort, V., Knibbe, C., Beslon, G., & Favrel, J. (2006). Simultaneous optimization of weights and structure of an RBF neural network. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *3871 LNCS*, 49–60. https://doi.org/10.1007/11740698_5

Li, F., Luo, Z., Rong, J., & Zhang, N. (2013). Interval multi-objective optimisation of structures using adaptive Kriging approximations. *Computers and Structures*, *119*, 68–84. https://doi.org/10.1016/j.compstruc.2012.12.028

Li, F., Luo, Z., & Sun, G. (2011). Reliability-based multiobjective design optimization under interval uncertainty. *CMES - Computer Modeling in Engineering and Sciences*, *74*(1), 39–64.

Li, F., Luo, Z., Sun, G., & Zhang, N. (2013). An uncertain multidisciplinary design optimization method using interval convex models. *Engineering Optimization*, *45*(6), 697–718. https://doi.org/10.1080/0305215X.2012.690871

Li, H., Chen, J., & Xiao, Y. (2013). Multi-objective optimization for laminated steel sheet forming process based on desirability function approach and reliability analysis. *Engineering Computations (Swansea, Wales)*, *30*(8), 1107–1127. https://doi.org/10.1108/EC-08-2012-0179

Li, Jian, Wang, H., & Kim, N. H. (2012). Doubly weighted moving least squares and its application to structural reliability analysis. *Structural and Multidisciplinary Optimization*, *46*(1), 69–82. https://doi.org/10.1007/s00158-011-0748-2

Li, Junhong, Sun, Y., Wang, Y., & Sun, J. (2022). Optimization of squeeze casting process of gearbox cover based on FEM and Box-Behnken design. *International Journal of Advanced Manufacturing Technology*, *118*(9–10), 3421–3430. https://doi.org/10.1007/s00170-021-08099-8

Li, M., & Azarm, S. (2008). Multiobjective collaborative robust optimization with interval uncertainty and interdisciplinary uncertainty propagation. *Journal of Mechanical Design, Transactions of the ASME*, *130*(8), 0814021–08140211. https://doi.org/10.1115/1.2936898

Li, M., Azarm, S., Williams, N., Al Hashimi, S., Almansoori, A., & Al Qasas, N. (2009). Integrated multi-objective robust optimization and sensitivity analysis with irreducible and reducible interval uncertainty. *Engineering Optimization*, *41*(10), 889–908. https://doi.org/10.1080/03052150902853005

Li, Q., Qiu, Z., & Zhang, X. (2017). Eigenvalue analysis of structures with interval parameters using the second-order Taylor series expansion and the DCA for QB. *Applied Mathematical Modelling*, *49*, 680–690. https://doi.org/10.1016/j.apm.2017.02.041

Li, Z. M., & Qiao, P. (2015). Buckling and postbuckling of anisotropic laminated cylindrical shells under combined external pressure and axial compression in thermal environments. *Composite Structures*, *119*, 709–726. https://doi.org/10.1016/j.compstruct.2014.09.039

Liefvendahl, M., & Stocki, R. (2006). A study on algorithms for optimization of Latin hypercubes. *Journal of Statistical Planning and Inference*, *136*(9), 3231–3247. https://doi.org/10.1016/j.jspi.2005.01.007

Lin, C. C., & Lee, Y. J. (2004). Stacking sequence optimization of laminated composite structures using genetic algorithm with local improvement. *Composite Structures*, *63*(3–4), 339–345. https://doi.org/10.1016/S0263-8223(03)00182-X

Lin, Y., Yang, Q., & Guan, G. (2019). Automatic design optimization of SWATH applying CFD and RSM model. *Ocean Engineering*, *172*(November 2018), 146–154. https://doi.org/10.1016/j.oceaneng.2018.11.044

Liu, R., Niu, X., Fan, J., Mu, C., & Jiao, L. (2015). An orthogonal predictive model-based dynamic multi-objective optimization algorithm. *Soft Computing*, *19*(11), 3083–3107. https://doi.org/10.1007/s00500-014-1470-y

Liu, Y., & Bai, X. (2013). Studying interconnections between two classes of two-stage fuzzy optimization problems. *Soft Computing*, *17*(4), 569–578. https://doi.org/10.1007/s00500-012-0925-2

Liu, Z. Z., Wang, T. S., & Li, J. F. (2015). A trigonometric interval method for dynamic response analysis of uncertain nonlinear systems. *Science China: Physics, Mechanics and Astronomy*, *58*(4). https://doi.org/10.1007/s11433-014-5641-8

Lopatin, A. V., & Morozov, E. V. (2017). Buckling of composite cylindrical shells with rigid end disks under hydrostatic pressure. *Composite Structures*, *173*, 136–143. https://doi.org/10.1016/j.compstruct.2017.03.109

Luo, J., & Sun, Y. (2020). Optimization of process parameters for the minimization of surface residual stress in turning pure iron material using central composite design. *Measurement*, *163*, 108001. https://doi.org/10.1016/j.measurement.2020.108001

Lv, M., Li, J., Niu, X., & Wang, J. (2022). Novel deterministic and probabilistic combined system based on deep learning and self-improved optimization algorithm for wind speed forecasting. *Sustainable Energy Technologies and Assessments*, *52*(PB), 102186. https://doi.org/10.1016/j.seta.2022.102186

Mallela, U. K., & Upadhyay, A. (2016). Buckling load prediction of laminated composite stiffened panels subjected to in-plane shear using artificial neural networks. *Thin-Walled Structures*, *102*, 158–164. https://doi.org/10.1016/j.tws.2016.01.025

McKay, M. D., Beckman, R. J., & Conover, W. J. (1979). Comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, *21*(2), 239–245. https://doi.org/10.1080/00401706.1979.10489755

Meckesheimer, M., Booker, A. J., Barton, R. R., & Simpson, T. W. (2002). Computationally inexpensive metamodel assessment strategies. *AIAA Journal*, *40*(10), 2053–2060. https://doi.org/10.2514/2.1538

Messager, T., Pyrz, M., Gineste, B., & Chauchot, P. (2002). Optimal laminations of thin underwater composite cylindrical vessels. *Composite Structures*, *58*(4), 529–537. https://doi.org/10.1016/S0263-8223(02)00162-9

Methods, C., Mech, A., Meng, Z., Pang, Y., Pu, Y., & Wang, X. (2020). New hybrid reliability-based topology optimization method combining fuzzy and probabilistic models for handling epistemic and aleatory uncertainties. *Computer Methods in Applied Mechanics and Engineering*, *363*, 112886. https://doi.org/10.1016/j.cma.2020.112886

Möller, B., & Beer, M. (2008). Engineering computation under uncertainty - Capabilities of non-traditional models. *Computers and Structures*, *86*(10), 1024–1041. https://doi.org/10.1016/j.compstruc.2007.05.041

Moon, C. J., Kim, I. H., Choi, B. H., Kweon, J. H., & Choi, J. H. (2010). Buckling of filament-wound composite cylinders subjected to hydrostatic pressure for underwater vehicle applications. *Composite Structures*, *92*(9), 2241–2251. https://doi.org/10.1016/j.compstruct.2009.08.005

Moore, R. E., Kearfott, R. B., & Cloud, M. J. (2009). *Introduction to interval analysis* (Vol. 110). Siam.

Morris, M. D., & Mitchell, T. J. (1995a). Exploratory designs for computational experiments. *Journal of Statistical Planning and Inference*, *43*(3), 381–402.

Morris, M. D., & Mitchell, T. J. (1995b). Exploratory designs for computational experiments. *Journal of Statistical Planning and Inference*, *43*(3), 381–402. https://doi.org/10.1016/0378-3758(94)00035-T

Muscolino, G., & Sofi, A. (2012). Stochastic analysis of structures with uncertain-but-bounded parameters via improved interval analysis. *Probabilistic Engineering Mechanics*, *28*, 152–163. https://doi.org/10.1016/j.probengmech.2011.08.011

Niven, I. (1961). Uniform distribution of sequences of integers. *Transactions of the American Mathematical Society*, *98*(1), 52–61.

Oberkampf, W., & Trucano, T. (2000). Validation methodology in computational fluid dynamics. *Fluids 2000 Conference and Exhibit*, 2549.

Olsson, A., Sandberg, G., & Dahlblom, O. (2003). On Latin hypercube sampling for structural reliability analysis. *Structural Safety*, *25*(1), 47–68. https://doi.org/10.1016/S0167-4730(02)00039-5

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

Owen, J. R. K. and A. B., & 1. (1996). Computer experiment. *Handbook of Statistics*, *13*, 261–308.

Özmen, A., & Weber, G. W. (2014). RMARS: Robustification of multivariate adaptive regression spline under polyhedral uncertainty. *Journal of Computational and Applied Mathematics*, *259*(PART B), 914–924. https://doi.org/10.1016/j.cam.2013.09.055

Pan, G., Ye, P., Wang, P., & Yang, Z. (2014). A sequential optimization sampling method for metamodels with radial basis functions. *Scientific World Journal*, *2014*. https://doi.org/10.1155/2014/192862

Pandey, N., & Thakur, C. (2020). Statistical Comparison of Response Surface Methodology – Based Central Composite Design and Hybrid Central Composite Design for Paper Mill Wastewater Treatment by Electrocoagulation. *Process Integration and Optimization for Sustainability*, *4*(4), 343–359.

Parnianifard, A., Azfanizam, A. S., Ariffin, M. K. A., Ismail, M. I. S., & Ale 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

Pawlak, M., & Rafajłowicz, E. (2009). Quasi-random sampling for signal recovery. *Nonlinear Analysis, Theory, Methods and Applications*, *71*(10), 4357–4363. https://doi.org/10.1016/j.na.2009.02.079

Pham, T. D., & Hong, W. (2022). Genetic algorithm using probabilistic-based natural selections and dynamic mutation ranges in optimizing precast beams. *Computers and Structures*, *258*, 106681. https://doi.org/10.1016/j.compstruc.2021.106681

Pishvaee, M. S., & Fazli Khalaf, M. (2016). Novel robust fuzzy mathematical programming methods. *Applied Mathematical Modelling*, *40*(1), 407–418. https://doi.org/10.1016/j.apm.2015.04.054

Pistone, G., & Rogantin, M. P. (2008). Indicator function and complex coding for mixed fractional factorial designs. *Journal of Statistical Planning and Inference*, *138*(3), 787–802. https://doi.org/10.1016/j.jspi.2007.02.007

Pitton, S. F., Ricci, S., & Bisagni, C. (2019). Buckling optimization of variable stiffness cylindrical shells through artificial intelligence techniques. *Composite Structures*, *230*, 111513. https://doi.org/10.1016/j.compstruct.2019.111513

Practice, T., & Fu, M. C. (2002). *d Optimization for Simulation :*

Qader, B. S., Supeni, E. E., Ariffin, M. K. A., & Talib, A. R. A. (2019). RSM approach for modeling and optimization of designing parameters for inclined fins of solar air heater. *Renewable Energy*, *136*, 48–68. https://doi.org/10.1016/j.renene.2018.12.099

Qasem, S. N., & Shamsuddin, S. M. (2011a). Memetic elitist Pareto differential evolution algorithm based radial basis function networks for classification problems. *Applied Soft Computing Journal*, *11*(8), 5565–5581. https://doi.org/10.1016/j.asoc.2011.05.002

Qasem, S. N., & Shamsuddin, S. M. (2011b). Radial basis function network based on time variant multi-objective particle swarm optimization for medical diseases diagnosis. *Applied Soft Computing Journal*, *11*(1), 1427–1438. https://doi.org/10.1016/j.asoc.2010.04.014

Qiu, Z., & Elishakoff, I. (1998). Antioptimization of structures with large uncertain-but-non-random parameters via interval analysis. *Computer Methods in Applied Mechanics and Engineering*, *152*(3–4), 361–372.

Qiu, Z., & Elishakoff, I. (2001). Anti-optimization technique - A generalization of interval analysis for nonprobabilistic treatment of uncertainty. *Chaos, Solitons and Fractals*, *12*(9), 1747–1759. https://doi.org/10.1016/S0960-0779(00)00102-8

Qiu, Z., Ma, L., & Wang, X. (2009). Non-probabilistic interval analysis method for dynamic response analysis of nonlinear systems with uncertainty. *Journal of Sound and Vibration*, *319*(1–2), 531–540. https://doi.org/10.1016/j.jsv.2008.06.006

Qiu, Z., & Wang, X. (2003). Comparison of dynamic response of structures with uncertain-but-bounded parameters using non-probabilistic interval analysis method and probabilistic approach. *International Journal of Solids and Structures*, *40*(20), 5423–5439. https://doi.org/10.1016/S0020-7683(03)00282-8

Qu, X., Venter, G., & Haftka, R. T. (2004). New formulation of minimum-bias central composite experimental design and Gauss quadrature. *Structural and Multidisciplinary Optimization*, *28*(4), 231–242. https://doi.org/10.1007/s00158-004-0433-9

Rafajłowicz, E., & Schwabe, R. (2006). Halton and Hammersley sequences in multivariate nonparametric regression. *Statistics and Probability Letters*, *76*(8), 803–812. https://doi.org/10.1016/j.spl.2005.10.014

Rao, P. M. V, & Rao, V. V. S. (2010). *Degradation model based on Tsai-Hill factors to model the progressive failure of fiber metal laminates*. https://doi.org/10.1177/0021998310387682

Rasmussen, C., C. W. (2006). *Gaussian processes for machine learning.* https://doi.org/10.1142/S0129065704001899

Recioui, A. (2014). Optimization of Antenna Arrays Using Different Strategies Based on Taguchi Method. *Arabian Journal for Science and Engineering*, *39*(2), 935–944. https://doi.org/10.1007/s13369-013-0644-8

Ren, Y., & Xiang, J. (2014). Crashworthiness uncertainty analysis of typical civil aircraft based on Box-Behnken method. *Chinese Journal of Aeronautics*, *27*(3), 550–557. https://doi.org/10.1016/j.cja.2014.04.020

Rippat, S. (1986). Numerical procedures for surface. *SIAM Journal on Scientific and Statistical Computing*, *7*(2), 639–660.

Rizk-Allah, R. M. (2019). An improved sine–cosine algorithm based on orthogonal parallel information for global optimization. *Soft Computing*, *23*(16), 7135–7161. https://doi.org/10.1007/s00500-018-3355-y

Roshanian, J., & Ebrahimi, M. (2013). Latin hypercube sampling applied to reliability-based multidisciplinary design optimization of a launch vehicle. *Aerospace Science and Technology*, *28*(1), 297–304. https://doi.org/10.1016/j.ast.2012.11.010

Ross, C. T. F. (2006). A conceptual design of an underwater vehicle. *Ocean Engineering*, *33*(16), 2087–2104. https://doi.org/10.1016/j.oceaneng.2005.11.005

Sagalevitch, A. (1998). *Experience of the use of manned submersibles in P . P . Shirshov Institute of Oceanology of Russian Academy of Sciences*. 403–407.

Saleem, M. M., & Somá, A. (2015). Design of experiments based factorial design and response surface methodology for MEMS optimization. *Microsystem Technologies*, *21*(1), 263–276. https://doi.org/10.1007/s00542-014-2186-8

Santoro, R., Muscolino, G., & Elishakoff, I. (2015). Optimization and anti-optimization solution of combined parameterized and improved interval analyses for structures with uncertainties. *Computers and Structures*, *149*, 31–42. https://doi.org/10.1016/j.compstruc.2014.11.006

Schuëller, G. I., & Jensen, H. A. (2008). Computational methods in optimization considering uncertainties - An overview. *Computer Methods in Applied Mechanics and Engineering*, *198*(1), 2–13. https://doi.org/10.1016/j.cma.2008.05.004

Science, N., Phenomena, C., Yan, D., Zheng, Y., Liu, W., Chen, T., & Chen, Q. (2022). Interval uncertainty analysis of vibration response of hydroelectric generating unit based on Chebyshev polynomial. *Chaos, Solitons and Fractals: The Interdisciplinary Journal of Nonlinear Science, and Nonequilibrium and Complex Phenomena*, *155*, 111712. https://doi.org/10.1016/j.chaos.2021.111712

Sevastianov, P. (2007). Numerical methods for interval and fuzzy number comparison based on the probabilistic approach and Dempster-Shafer theory. *Information Sciences*, *177*(21), 4645–4661. https://doi.org/10.1016/j.ins.2007.05.001

Shahabad, P. K., Anamagh, M. R., & Bediz, B. (2022). Design of laminated conical shells using spectral Chebyshev method and lamination parameters. *Composite Structures*, *281*(November 2021), 114969. https://doi.org/10.1016/j.compstruct.2021.114969

Shan, S., & Wang, G. G. (2010). Metamodeling for high dimensional simulation-based design problems. *Journal of Mechanical Design, Transactions of the ASME*, *132*(5), 0510091–05100911. https://doi.org/10.1115/1.4001597

Shang, X., Chao, T., Ma, P., & Yang, M. (2020). An efficient local search-based genetic algorithm for constructing optimal Latin hypercube design. *Engineering Optimization*, *52*(2), 271–287. https://doi.org/10.1080/0305215X.2019.1584618

Shen, K., & Pan, G. (2019). Buckling Optimization of Composite Cylinders for Underwater Vehicle Applications Under Tsai-Wu Failure Criterion Constraint. *Journal of Shanghai Jiaotong University (Science)*, *24*(4), 534–544. https://doi.org/10.1007/s12204-019-2087-1

Shiroud, B., Oliaei, E., & Shayesteh, H. (2017). Simulation of mechanical behavior and optimization of simulated injection molding process for PLA based antibacterial composite and nanocomposite bone screws using central composite design. *Journal of the Mechanical Behavior of Biomedical Materials*, *65*, 160–176. https://doi.org/10.1016/j.jmbbm.2016.08.008

Simpson, T. W., Mauery, T. M., Korte, J. J., & Mistree, F. (2001). Kriging models for global approximation in simulation-based multidisciplinary design optimization. *AIAA Journal*, *39*(12), 2233–2241. https://doi.org/10.2514/2.1234

Sivula, T., Magnusson, M., Matamoros, A. A., & Vehtari, A. (2020). *Uncertainty in Bayesian Leave-One-Out Cross-Validation Based Model Comparison*. *March*. http://arxiv.org/abs/2008.10296

Smith, C. S. (1991). Design of submersible pressure hulls in composite materials. *Marine Structures*, *4*(2), 141–182. https://doi.org/10.1016/0951-8339(91)90018-7

Su, Y., Fu, G., Wan, B., Yu, T., Zhou, W., & Wang, X. (2019). Fatigue reliability design for metal dual inline packages under random vibration based on response surface method. *Microelectronics Reliability*, *100–101*(May), 113404. https://doi.org/10.1016/j.microrel.2019.113404

Subasi, A., Sahin, B., & Kaymaz, I. (2016). Multi-objective optimization of a honeycomb heat sink using Response Surface Method. *International Journal of Heat and Mass Transfer*, *101*, 295–302. https://doi.org/10.1016/j.ijheatmasstransfer.2016.05.012

Sun, G., Li, G., Gong, Z., He, G., & Li, Q. (2011). Radial basis functional model for multi-objective sheet metal forming optimization. *Engineering Optimization*, *43*(12), 1351–1366. https://doi.org/10.1080/0305215X.2011.557072

Taflanidis, A. A., & Cheung, S. (2012). Stochastic sampling using moving least squares response surface approximations. *Probabilistic Engineering Mechanics*, *28*, 216–224. https://doi.org/10.1016/j.probengmech.2011.07.003

Tang, J. F., Wang, D. W., Fung, R. Y. K., & Yung, K.-L. (2004). Understanding of fuzzy optimization: theories and methods. *Journal of Systems Science and Complexity*, *17*(1), 117–136.

Tekin, E., & Sabuncuoglu, I. (2004). Simulation optimization: A comprehensive review on theory and applications. *IIE Transactions (Institute of Industrial Engineers)*, *36*(11), 1067–1081. https://doi.org/10.1080/07408170490500654

Trinca, L. A., & Gilmour, S. G. (2000). An algorithm for arranging response surface designs in small blocks. *Computational Statistics and Data Analysis*, *33*(1), 25–43. https://doi.org/10.1016/S0167-9473(99)00033-X

Upputuri, H. B., & Nimmagadda, V. S. (2020). Optimization of drilling process parameters used in machining of glass fiber reinforced epoxy composite. *Materials Today: Proceedings*, *23*(xxxx), 594–599. https://doi.org/10.1016/j.matpr.2019.05.415

Vandewoestyne, B., & Cools, R. (2010). On the convergence of quasi-random sampling/importance resampling. *Mathematics and Computers in Simulation*, *81*(3), 490–505. https://doi.org/10.1016/j.matcom.2009.09.004

Varaee, H., Shishegaran, A., & Reza, M. (2021). The life-cycle cost analysis based on probabilistic optimization using a novel algorithm. *Journal of Building Engineering*, *43*(July), 103032. https://doi.org/10.1016/j.jobe.2021.103032

Vehtari, A., Mononen, T., Tolvanen, V., Sivula, T., & Winther, O. (2016). Bayesian leave-one-out cross-validation approximations for Gaussian latent variable models. *Journal of Machine Learning Research*, *17*, 1–38.

Vehtari, A., Simpson, D. P., Yao, Y., & Gelman, A. (2019). Limitations of "Limitations of Bayesian Leave-one-out Cross-Validation for Model Selection." *Computational Brain and Behavior*, *2*(1), 22–27. https://doi.org/10.1007/s42113-018-0020-6

Victoire, T. A. A., & Jeyakumar, A. E. (2004). Hybrid PSO-SQP for economic dispatch with valve-point effect. *Electric Power Systems Research*, *71*(1), 51–59. https://doi.org/10.1016/j.epsr.2003.12.017

Vosoughi, A. R., & Gerist, S. (2014). New hybrid FE-PSO-CGAs sensitivity base technique for damage detection of laminated composite beams. *Composite Structures*, *118*(1), 68–73. https://doi.org/10.1016/j.compstruct.2014.07.012

Vu-Bac, N., Lahmer, T., Zhuang, X., Nguyen-Thoi, T., & Rabczuk, T. (2016). A software framework for probabilistic sensitivity analysis for computationally expensive models. *Advances in Engineering Software*, *100*, 19–31. https://doi.org/10.1016/j.advengsoft.2016.06.005

Walden, B. B., & Brown, R. S. (2004). A replacement for the Alvin submersible. *Marine Technology Society Journal*, *38*(2), 85–91. https://doi.org/10.4031/002533204787522721

Wang, G. G. (2003). Adaptive response surface method using inherited Latin hypercube design points. *Journal of Mechanical Design, Transactions of the ASME*, *125*(2), 210–220. https://doi.org/10.1115/1.1561044

Wang, G. G., & Shan, S. (2007). Review of metamodeling techniques in support of engineering design optimization. *Journal of Mechanical Design, Transactions of the ASME*, *129*(4), 370–380. https://doi.org/10.1115/1.2429697

Wang, K., & Zheng, Y. J. (2012). A new particle swarm optimization algorithm for fuzzy optimization of armored vehicle scheme design. *Applied Intelligence*, *37*(4), 520–526. https://doi.org/10.1007/s10489-012-0345-0

Wang, L., Xiong, C., Wang, X., Xu, M., & Li, Y. (2018). A dimension-wise method and its improvement for multidisciplinary interval uncertainty analysis. *Applied Mathematical Modelling*, *59*, 680–695. https://doi.org/10.1016/j.apm.2018.02.022

Wang, Xiaoou, Liu, Y., & Antonsson, E. K. (1999). Fitting functions to data in high dimensional design space. *Proceedings of the ASME Design Engineering Technical Conference*, *1*(Lm), 623–630. https://doi.org/10.1115/DETC99/DAC-8622

Wang, Xuzhu, & Kerre, E. E. (2001a). Reasonable properties for the ordering of fuzzy quantities (I). *Fuzzy Sets and Systems*, *118*(3), 387–405. https://doi.org/10.1016/S0165-0114(99)00063-9

Wang, Xuzhu, & Kerre, E. E. (2001b). Reasonable properties for the ordering of fuzzy quantities (II). *Fuzzy Sets and Systems*, *118*(3), 387–405. https://doi.org/10.1016/S0165-0114(99)00063-9

Weber, G. W., Batmaz, I., Köksal, G., Taylan, P., & Yerlikaya-Özkurt, F. (2012). CMARS: A new contribution to nonparametric regression with multivariate adaptive regression splines supported by continuous optimization. *Inverse Problems in Science and Engineering*, *20*(3), 371–400. https://doi.org/10.1080/17415977.2011.624770

Wei, X., Wu, Y. Z., & Chen, L. P. (2012). A new sequential optimal sampling method for radial basis functions. *Applied Mathematics and Computation*, *218*(19), 9635–9646. https://doi.org/10.1016/j.amc.2012.02.067

Wen, Y., Yue, X., Hunt, J. H., & Shi, J. (2018). Feasibility analysis of composite fuselage shape control via finite element analysis. *Journal of Manufacturing Systems*, *46*, 272–281. https://doi.org/10.1016/j.jmsy.2018.01.008

Wen, Y., Yue, X., Hunt, J. H., & Shi, J. (2019). Virtual assembly and residual stress analysis for the composite fuselage assembly process. *Journal of Manufacturing Systems*, *52*(October 2018), 55–62. https://doi.org/10.1016/j.jmsy.2019.04.001

Wetter, M., & Wright, J. (2004). A comparison of deterministic and probabilistic optimization algorithms for nonsmooth simulation-based optimization. *Building and Environment*, *39*, 989–999. https://doi.org/10.1016/j.buildenv.2004.01.022

Witek-Krowiak, A., Chojnacka, K., Podstawczyk, D., Dawiec, A., & Pokomeda, K. (2014). Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process. *Bioresource Technology*, *160*, 150–160. https://doi.org/10.1016/j.biortech.2014.01.021

Wu, H. C. (2007). The Karush-Kuhn-Tucker optimality conditions for the optimization problem with fuzzy-valued objective function. *Mathematical Methods of Operations Research*, *66*(2), 203–224. https://doi.org/10.1007/s00186-007-0156-y

Wu, J., Gao, J., Luo, Z., & Brown, T. (2016). Robust topology optimization for structures under interval uncertainty. *Advances in Engineering Software*, *99*, 36–48. https://doi.org/10.1016/j.advengsoft.2016.05.002

Wu, J., Luo, Z., Li, H., & Zhang, N. (2017). A new hybrid uncertainty optimization method for structures using orthogonal series expansion. *Applied Mathematical Modelling*, *45*, 474–490. https://doi.org/10.1016/j.apm.2017.01.006

Wu, J., Luo, Z., Zhang, N., & Zhang, Y. (2015). A new interval uncertain optimization method for structures using Chebyshev surrogate models. *Computers and Structures*, *146*, 185–196. https://doi.org/10.1016/j.compstruc.2014.09.006

Wu, J., Luo, Z., Zhang, Y., & Zhang, N. (2014). An interval uncertain optimization method for vehicle suspensions using Chebyshev metamodels. *Applied Mathematical Modelling*, *38*(15–16), 3706–3723. https://doi.org/10.1016/j.apm.2014.02.012

Wu, J., Zhang, Y., Chen, L., & Luo, Z. (2013). A Chebyshev interval method for nonlinear dynamic systems under uncertainty. *Applied Mathematical Modelling*, *37*(6), 4578–4591. https://doi.org/10.1016/j.apm.2012.09.073

Xia, B., Yu, D., & Liu, J. (2013). Interval and subinterval perturbation methods for a structural-acoustic system with interval parameters. *Journal of Fluids and Structures*, *38*, 146–163. https://doi.org/10.1016/j.jfluidstructs.2012.12.003

Xing, Z., Qu, R., Zhao, Y., Fu, Q., Ji, Y., & Lu, W. (2019). Identifying the release history of a groundwater contaminant source based on an ensemble surrogate model. *Journal of Hydrology*, *572*(January), 501–516. https://doi.org/10.1016/j.jhydrol.2019.03.020

Xu, S., Feng, N., Liu, K., Liang, Y., & Liu, X. (2021). A weighted fuzzy process neural network model and its application in mixed-process signal classification. *Expert Systems with Applications*, *172*(April 2019), 114642. https://doi.org/10.1016/j.eswa.2021.114642

Yang, L., Wang, J., Sun, X., & Xu, M. (2019). Multi-objective optimization design of spiral demister with punched holes by combining response surface method and genetic algorithm. *Powder Technology*, *355*, 106–118. https://doi.org/10.1016/j.powtec.2019.07.030

Yang, X., Tartakovsky, G., & Tartakovsky, A. (2018). Physics-Information-Aided Kriging: Constructing Covariance Functions using Stochastic Simulation Models. *ArXiv Preprint ArXiv:1809.03461*. http://arxiv.org/abs/1809.03461

Yen, G. G. (2006). Multi-objective evolutionary algorithm for radial basis function neural network design. *Studies in Computational Intelligence*, *16*, 221–239. https://doi.org/10.1007/11399346_10

Yilmaz, I., & Kaynar, O. (2011). Multiple regression, ANN (RBF, MLP) and ANFIS models for prediction of swell potential of clayey soils. *Expert Systems with Applications*, *38*(5), 5958–5966. https://doi.org/10.1016/j.eswa.2010.11.027

Yin, X., & Chen, W. E. I. (2006). Enhanced Sequential Optimization and Reliability Assessment method for probabilistic optimization with varying design variance. *Structure and Infrastructure Engineering*, *2*, 261–275. https://doi.org/10.1080/15732470600590317

Yondo, R., & Andr, E. (2018). *Progress in Aerospace Sciences A review on design of experiments and surrogate models in aircraft real-time and many-query aerodynamic analyses Probability of Improvement Prediction Error Sum of Squares*. *96*(March 2017), 23–61. https://doi.org/10.1016/j.paerosci.2017.11.003

Youn, B. D., & Choi, K. K. (2004). A new response surface methodology for reliability-based design optimization. *Computers and Structures*, *82*(2–3), 241–256. https://doi.org/10.1016/j.compstruc.2003.09.002

Yu, J., Wang, Q., Zhang, Z., & Li, X. (2017). Multi-objective optimizations of multidirectional forming mold based on fractional factorial design. *International Journal of Advanced Manufacturing Technology*, *88*(1–4), 1151–1160. https://doi.org/10.1007/s00170-016-8844-5

Yue, R. X. (2001). A comparison of random and quasirandom points for nonparametric response surface design. *Statistics and Probability Letters*, *53*(2), 129–142. https://doi.org/10.1016/S0167-7152(01)00065-7

Zadeh, L. A. (1965). Electrical engineering at the crossroads. *IEEE Transactions on Education*, *8*(2), 30–33.

Zereik, E., Bibuli, M., Mišković, N., Ridao, P., & Pascoal, A. (2018). Challenges and future trends in marine robotics. *Annual Reviews in Control*, *46*, 350–368. https://doi.org/10.1016/j.arcontrol.2018.10.002

Zhang, D., Han, X., Jiang, C., Liu, J., & Li, Q. (2017). Time-dependent reliability analysis through response surface method. *Journal of Mechanical Design, Transactions of the ASME*, *139*(4), 1–12. https://doi.org/10.1115/1.4035860

Zhang, J., Xiao, M., Gao, L., & Fu, J. (2018). A novel projection outline based active learning method and its combination with Kriging metamodel for hybrid reliability analysis with random and interval variables. *Computer Methods in Applied Mechanics and Engineering*, *341*, 32–52. https://doi.org/10.1016/j.cma.2018.06.032

Zhang, S., He, W., Chen, D., Chu, J., & Fan, H. (2019). A dynamic human reliability assessment approach for manned submersibles using PMV-CREAM. *International Journal of Naval Architecture and Ocean Engineering*, *11*(2), 782–795. https://doi.org/10.1016/j.ijnaoe.2019.03.002

Zhang, W. G., & Goh, A. T. C. (2013). Multivariate adaptive regression splines for analysis of geotechnical engineering systems. *Computers and Geotechnics*, *48*, 82–95. https://doi.org/10.1016/j.compgeo.2012.09.016

Zhang, W., & Goh, A. T. C. (2016). Multivariate adaptive regression splines and neural network models for prediction of pile drivability. *Geoscience Frontiers*, *7*(1), 45–52. https://doi.org/10.1016/j.gsf.2014.10.003

Zhang, W., Wu, C., Li, Y., Wang, L., & Samui, P. (2021). Assessment of pile drivability using random forest regression and multivariate adaptive regression splines. *Georisk*, *15*(1), 27–40. https://doi.org/10.1080/17499518.2019.1674340

Zhang, Y. (2019). An accurate and stable RBF method for solving partial differential equations. *Applied Mathematics Letters*, *97*, 93–98. https://doi.org/10.1016/j.aml.2019.05.021

Zhao, K., Xue, H., Yang, F., & Zhao, L. (2019). Probability prediction of crack growth rate of environmentally assisted cracks of nickel-based alloys based on Latin hypercube sampling. *International Journal of Pressure Vessels and Piping*, *172*(March), 391–396. https://doi.org/10.1016/j.ijpvp.2019.04.005

Zhao, L., Choi, K. K., Lee, I., & Gorsich, D. (2013). Conservative Surrogate Model using Weighted Kriging Variance for Sampling-based RBDO. *Journal of Mechanical Design*, *135*(9), 91003. https://doi.org/10.1090/dimacs/029/20

Zhao, M., & Cui, W. C. (2007). Application of the optimal Latin hypercube design and radial basis function network to collaborative optimization. *Journal of Marine Science and Application*, *6*(3), 24–32. https://doi.org/10.1007/s11804-007-7012-6

Zhao, R., Wang, Y., Hu, P., Jelodar, H., Yuan, C., Li, Y. C., Masood, I., & Rabbani, M. (2019). Selfish herds optimization algorithm with orthogonal design and information update for training multi-layer perceptron neural network. In *Applied Intelligence* (Vol. 49, Issue 6). Applied Intelligence. https://doi.org/10.1007/s10489-018-1373-1

Zhao, Z., Han, X., Jiang, C., & Zhou, X. (2010). A nonlinear interval-based optimization method with local-densifying approximation technique. *Structural and Multidisciplinary Optimization*, *42*(4), 559–573. https://doi.org/10.1007/s00158-010-0501-2

ZHENG, G., & YANG, X. (2019). Studies of the resistance optimization of underwater vehicle based on multiple-speed approximate model. *MATEC Web of Conferences*, *272*, 1029.

Zhou, J., Cheng, S., & Li, M. (2012). Sequential quadratic programming for robust optimization with interval uncertainty. *Journal of Mechanical Design, Transactions of the ASME*, *134*(10), 1–13. https://doi.org/10.1115/1.4007392

Zhou, Y. T., Jiang, C., & Han, X. (2006). Interval and subinterval analysis methods of the structural analysis and their error estimations. *International Journal of Computational Methods*, *3*(2), 229–244. https://doi.org/10.1142/S0219876206000771

Zu, L., Koussios, S., & Beukers, A. (2010). Shape optimization of filament wound articulated pressure vessels based on non-geodesic trajectories. *Composite Structures*, *92*(2), 339–346. https://doi.org/10.1016/j.compstruct.2009.08.013