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Machine Learning Aided Optimization of Non-Metallic Seals in Downhole Tools

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Abstract

Machine learning-based optimization analysis is conducted to improve the performance and reliability of non-metallic seals that undergo dynamic loading. Non-metallic seals, mostly made from elastomeric materials such as rubber, are widely used in the oil and gas industry due to their combination of hyper-elastic behavior and lack of plastic deformation under pressure and temperature cycles. However, these elastomeric materials could soften at elevated temperatures or during cyclic loading which makes them more prone to extrude from the seal region. For simple seals such as O-rings, thermoplastic anti-extrusion backup rings can be used to resist rubber extrusion. For more complex molded or bonded seals subject to cyclic loads and temperature cycles, minimizing the rubber damage and maintaining the seal integrity becomes more challenging as there may be inadequate room for backup rings. Additionally, the rubber may also experience repeated long stroke lengths during service which can cause surface abrasion. Non-metallic seals are extensively used in Sand Control Tools, a class of completion equipment. In the development of these molded and bonded seals, advanced optimization analysis techniques are important to make the seal design sufficiently robust to meet the stringent requirements of industry codes and regulations. Machine learning-based optimization analysis allows for increasing the seal performance and reliability. The Mullins effect is included in the elastomeric material model to capture the material softening effects under cyclic loading. Machine learning-based optimization starts with a feasible design space that is defined based on the controlling design parameters related to the geometry of the seal. Comprehensive Finite Element Analysis is performed on each design sample under the target cyclic load and temperature cycles. The key response parameters of the non-metallic seal are selected as the principal strain and the contact stress in the rubber which together indicate the damage and seal-ability states of the design. A Performance Objective Index is defined as a function of the key response parameters. The FEA results covering the entire design space provide the simulation-driven training data to build the surrogate model using multi-layer neural networks. The optimum design solution is found from the surrogate model which correlates the Performance Objective Index to the design parameters. The results of this study reveal that the performance of the seal is greatly affected by the ratio of the elastomeric seal volume to the gland volume into which the seal is molded. As opposed to the base design, the optimum design shows a solid performance with no signs of extrusion when the principal strain of the rubber is kept below the elongation limit throughout the load cycles, and when sufficient contact stress is developed to maintain the seal.

Keywords

Machine Learning, Optimization, FEA, seals, Neural Networks, Downhole Tools, Mullins Effect

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1 Introduction

Non-metallic seals have broad applications in the oil and gas industry for both static and dynamic sealing conditions [1]. Elastomeric material such as rubber are widely used in the form of either bonded (molded) or unbonded seals depending on the application. Bonded seals are mostly preferred for applications where there is considerable load and temperature cycles as well as repeated strokes and seal movements. Unbonded seals like conventional O-rings are more appropriate for designs with limited load cycles and seal movements. In this case, thermoplastic material, such as PTFE or PEEK, are typically used as backup rings to prevent seal extrusion particularly under high pressure and high temperature (HPHT) conditions [2]. Thermoplastic materials are also directly used as dynamic seals where their low frictional coefficient and intrinsic self-lubricity become advantageous.

Figure 1 shows examples of unbonded and bonded elastomeric seals. As seen, the bonded seals cannot be supported by backup rings, thus may extrude under high differential pressure and temperature cycles. Open and close of the tubing can also promote seal movement and extrusion.

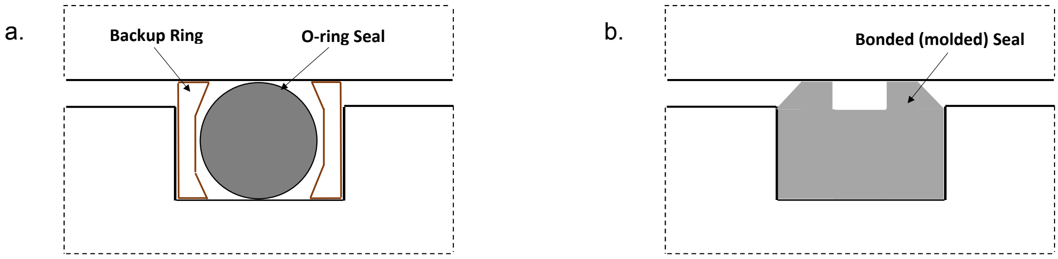

Figure 1. Examples of Unbonded and Bonded Seals.

To maintain the seal integrity, the strength and seal-ability criteria should be both satisfied respectively by limiting the rubber strain below the material elongation capacity and keeping the seal contact stress above the applied pressure level. To achieve a robust seal performance and reliability, advanced design optimization analyses become necessary. Due to complexity of the physics-based models and inherent variations in non-metallic material properties particularly at elevated temperature and hostile operating environment, more attentions have been recently paid to incorporating data-driven models in seal design development process [3] or combined data and physics-based models for design optimization [4].

In this paper, a machine-learning based design optimization analysis is conducted on a bonded seal used in Multi-Closing Sleeves (MCS) for sand control tools as a class of completion equipment. The elastomeric material modelling under cyclic loads is first discussed. The design parameters are then defined to form a feasible and practical design space. Finite element analysis is conducted all design samples. A Performance Objective Index (POI) is calculated as a function of the key response parameters of the seal for multi-objective optimization. Machine learning analysis is conducted to build a surrogate model of the POI using Artificial Neural Networks (ANN). The optimum design solution is found from the surrogate model and the results are compared against the original design to better highlight the seal performance improvement obtained by the optimization analysis.

2 Elastomeric Material Modelling Under Cyclic Loads

The cyclic loading effects on rubbers and elastomers can be summarized into five main effects: 1) stress-softening at unloading or so-called Mullins effect, 2) hysteresis effect in the first loading cycles (stabilization occurs in next cycles), 3) stress relaxation during stable cycles, 4) permanent set or residual strain, and 5) creep of residual strain. While it is computationally challenging to include all these effects, the stress softening at unloading or Mullins effect was included in our computational model to capture the rubber softening and increase in strain which may results in potential damage and extrusion of the rubber under pressure and temperature cycles.

Figure 2 presents a typical cyclic behaviour of rubbers [5], and the results of Simple Tension (ST), Planar Tension (PT), and Equi-Biaxial tension (EB) tests. The tests results covering different strain ranges with unloading cycles are used to calibrate the Mullins parameters.

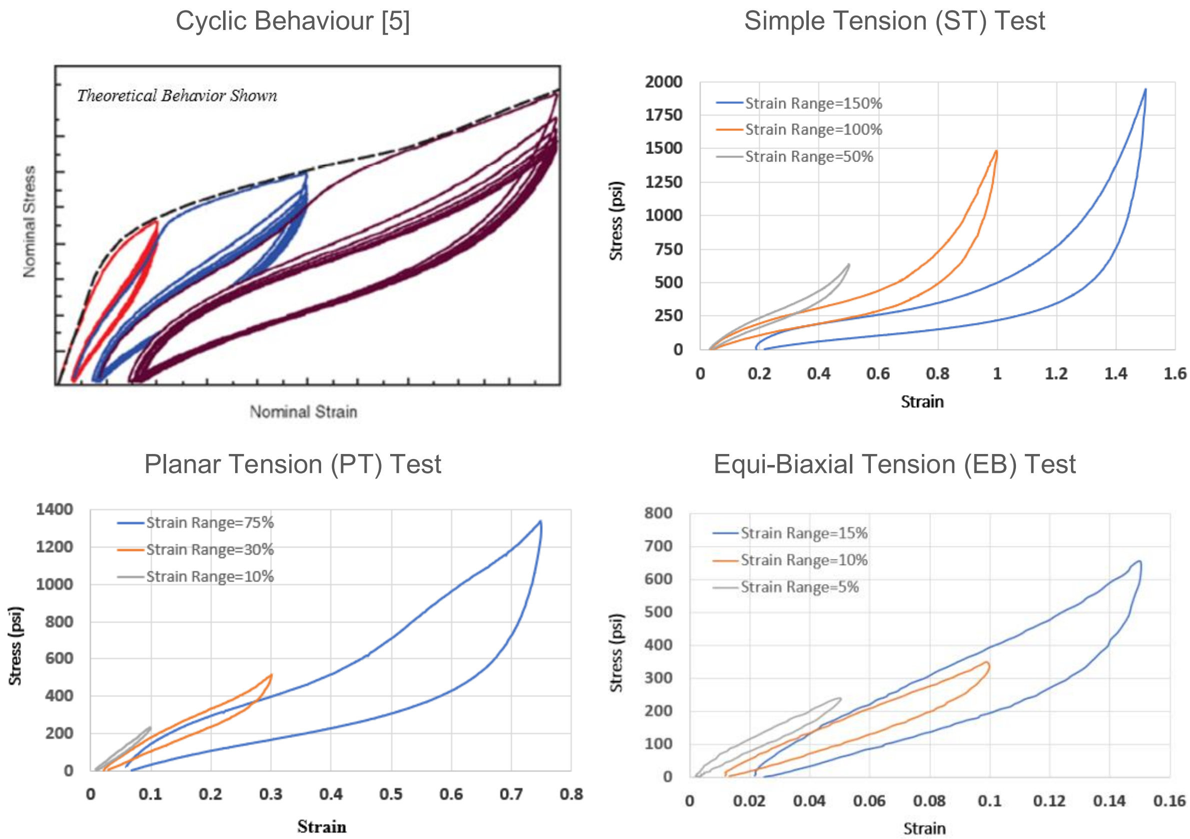

Figure 2. Examples of Unbonded and Bonded Seals.

3 Design Space and Parameters

Figure 3 shows the design space and parameters for a bonded seal in MCS. The width of the seal (W) and the inclination angle (β) were defined as the main design parameters controlling the seal geometry. Other dimensions such as the seal gland (L and H) and the extrusion gap (e) were taken as fixed per design requirements. The void index is defined as the area of the void within the seal gland divided by the total area of the gland, which can be expressed as a nonlinear function of the parameters W and β. As will be discussed, using the void index instead of the original design parameters results in a better correlation with the POI surrogate and reduces the design space dimension.

Manufacturing constrains as well as domain knowledge were used to define a feasible and practical design space. Twenty-four different design samples were selected from the design space for Finite Element Analysis (FEA).

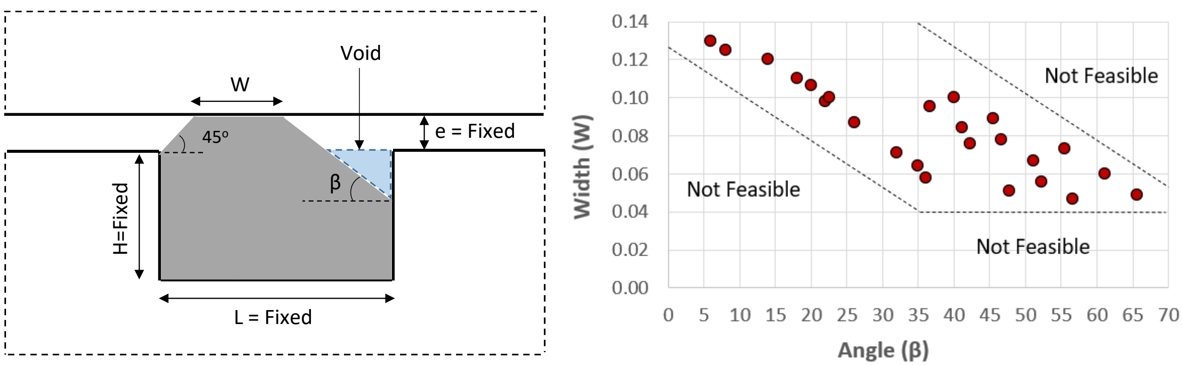

Figure 3. Design space and parameters.

4 Finite Element Analysis – Physics Based Model

Finite element analysis was conducted on all twenty-four design samples per API 19AC test loading protocol. Internal and external pressure cycles of about 10,000 psi were applied at 325°F temperature. The analysis revealed the seal key responses including the rubber strain and contact stress for each design sample. Figure 4 shows the results for one of the bonded seals in MCS for both internal and external pressures.

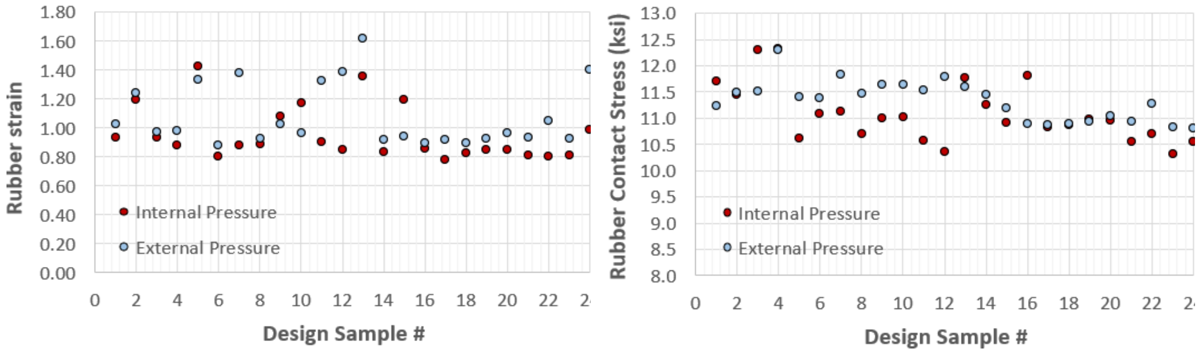

Figure 4. Key responses of the bonded seal.

The performance objective index (POI) of the seal is defined based on the seal key responses as expressed in Equation (1). The parameter *Wi* indicates the weight factor. To minimize the risk of rubber damage, we've assumed W_1=2 and W_2=1. The $(POI)_{Rubber\ Strain}$ is defined as the maximum rubber strain normalized to the rubber strain limit (100%). The $(POI)_{Contact\ Stress}$ is defined as the target pressure of 10,000 psi divided by the contact stress developed at the seal surface. It can be inferred that the POI defined in the following form offers a penalty function or failure index. The objective of the design optimization is to minimize the seal POI.

$$(POI)_{Seal} = W1 \times (POI)_{Rubber\ Strain} + W2 \times (POI)_{Contact\ Stress} \quad (1)$$

5 Machine Learning Optimization Analysis – Data Model

Figure 5 shows the layout of a neural network used as the machine learning model to perform a regression analysis. The analysis results of the physics-based model are used as input data to train the neural network. The input data consists of a design parameter vector X = (W, β) and its corresponding label Y = (POI)Seal. The output of the neural network is a surrogate model (data model) which correlates the POI to the design parameters.

Figure 6 presents the surrogate model in a 2D contour format where we can find the optimum design range resulting in minimum POI within the feasible design range. The initial optimization search shows the optimum seal width and the angel about 0.1 inch and 18 deg, respectively. This is corresponding to a void index of about 0.3.

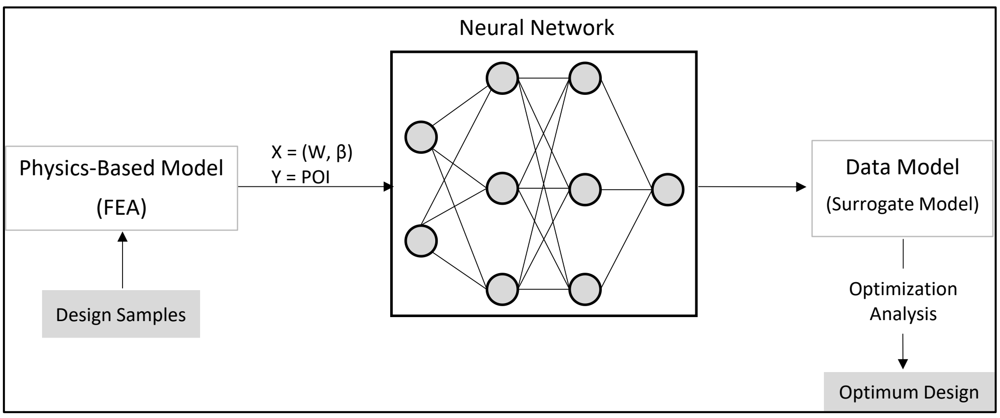

Figure 5. Neural Network Analysis Layout.

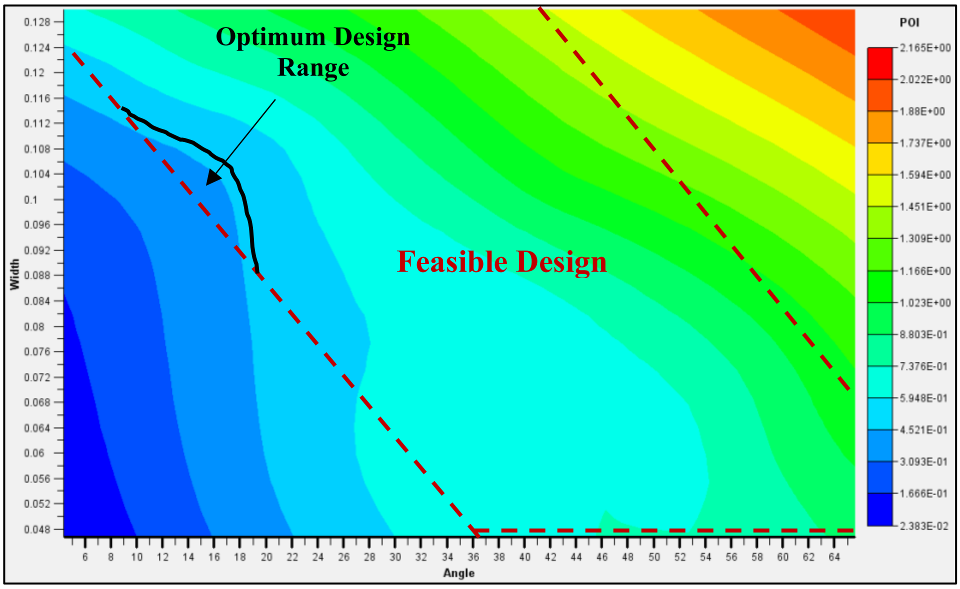

Figure 6. POI Surrogate (2D) vs Design Parameters.

To better see the POI correlation with the design parameter(s) and variations in the design space, the void index is defined as a nonlinear function of the original design parameters to reduce the design space dimension from 2D to 1D.

Figure 7 presents the POI variations vs void index where it is seen that all the data points are collapsing around a polynomial master curve. The results show the optimum range for the void index as 0.3-0.35 where POI is minimum. Interestingly, the original design which repeatedly failed during the experimental tests is seen to have a void index of 0.147 corresponding to POI = 0.9 which is far from the optimum design and implies a high chance of failure.

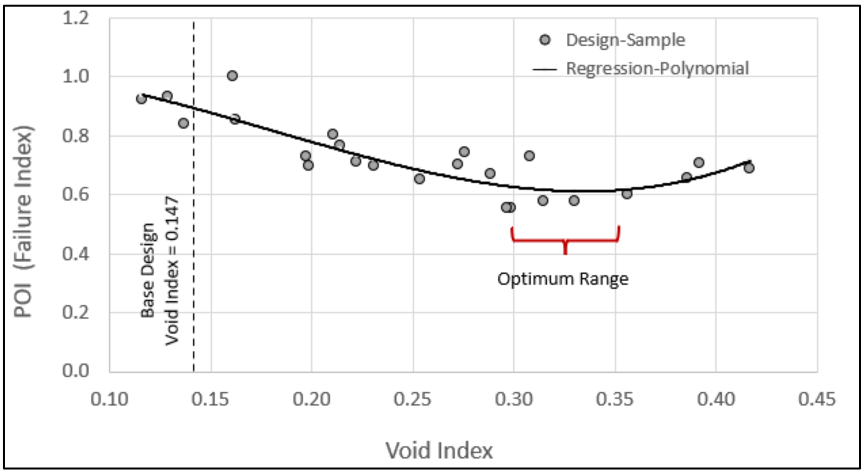

Figure 7. POI Surrogate (1D) vs Void Index.

6 Optimum Seal Performance

As shown in Figure 8, the rubber strain of the optimum seal was compared with the original or base design under the target pressure (10,000 psi) and temperature (325ºF). The desirable rubber strain limit was set as 100%. The original design showed some signs of extrusion and high rubber strain (120%), while the optimum design proved a robust performance with acceptable rubber strain (86%) and no signs of potential extrusion. The contact stress right after the assembly and before pressure application was also studied. A more uniform contact stress was seen at the optimum design compared to that of the original design implying a better ratio of the rubber volume to the seal gland volume.

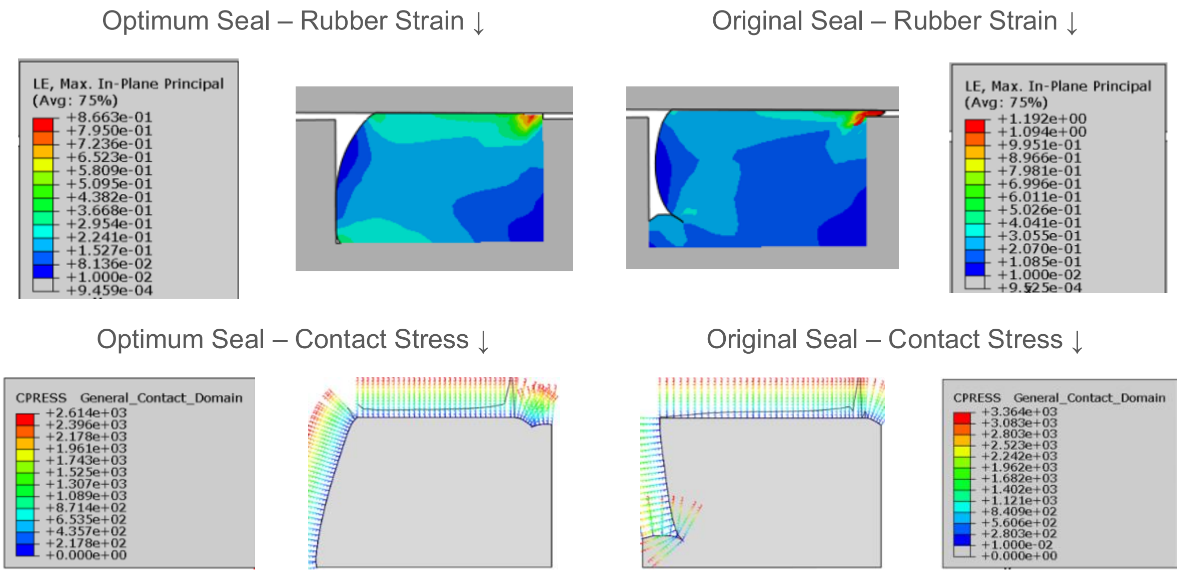

Figure 8. Comparative Performance - Optimum vs Original Seal.

7 Conclusions

The combination of the physics-based model using finite element analysis and the data-driven model using machine learning analysis offered a powerful design optimization analysis technique capable of exploring the design space thoroughly and efficiently.

This study demonstrated that proper profiling of the bonded seal is an effective method to improve the seal integrity. The analysis revealed that the bonded seal performance is greatly affected by the seal void index which is indeed a measure of seal volume over the gland volume into which the seal is molded.

For the bonded seal studied in this paper, the optimum range of the seal void index was found as 0.3-0.35 minimizing the risk of rubber damage and extrusion. The analysis per API 19AC loading plan showed a robust performance of the optimum seal where the rubber strain under 10,000 psi pressure at 325^{o}F temperature was kept below the desirable limit of 100% with no sign of a potential extrusion. In contrast, the original design experienced large rubber strain of 120% with strong signs of extrusion and local damage.

8 References

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