

Design of an Expandable Base Pipe Using a Genetic Algorithm-Based Multi-Objective Optimization Method

Allan Zhong, John Gano and Dingding Chen
Halliburton, Carrollton, TX, USA

Abstract: Perforated base pipe is an important component in a completion system. Field applications dictate that a good perforated base-pipe design should have good expandability and good post-expansion tensile strength and collapse strength. High fidelity FEA models for evaluation of expandable base pipes have been developed; however, to optimize hole pattern design (size, shape, placement pattern) of a given size base pipe, even numerically, can be expensive and time consuming. Using FEA models and a genetic algorithm-based multi-objective optimization scheme, the authors have successfully optimized a perforated base pipe in a relatively short period of time. The significant improvement over standard design has been demonstrated by physical tests. Several aspects of the optimization process will be presented in this paper.

Keywords: Expandable completion, basepipe, expansion, optimization, constraint, genetic algorithm

1. Introduction

The expandable completion system discussed in this paper provides a means of improving sand-control completion functionality and complements the existing sand control technology portfolio. It uses perforated and solid expandable base pipe with easy and quick connections, superior filtration material, and unique annular barrier technology. The expansion is realized via hydro-mechanical expansion methodology. See **Figure 1** (Echols, 2002). The perforated base pipe with filtering material forms a sand screen with the main functions of limiting sand mobility within the formation, minimizing the occurrence of borehole collapse, and facilitating production control. Therefore, the perforated basepipe is an important part of this system. Field applications dictate that a good perforated basepipe design should have good expandability and good post expansion tensile and collapse strength. In this paper, the focus is on the numerical optimization of the design of perforated base pipe.

Finite element simulation of the expansion of perforated base pipe has become a standard practice in the design of expandable systems. Due to the strong nonlinearity involved, the computation is typically intensive, and takes a relatively long time. This prevents effective application of FEA in large scale optimization of the perforated base pipe. Instead, the authors use surrogate model ensembles for sparse data (Chen, 2007) to achieve a true design optimization based on limited FEA simulations.

The discussion in the paper is organized as follows:

1. *Section 2* — simulation of base pipe expansion
2. *Section 3* — the optimization technique
3. *Section 4* — aspects of design optimization
4. *Section 5* — concluding remarks.

2. Simulations for Design of Expandable Perforated Base Pipe

For a given size of perforated base pipe, the main design parameters that influence its performance include selection of materials (ductility, fracture strength, corrosion resistance etc., typically determined a priority between designers and metallurgists), expansion-cone design, and hole design (size, shape, placement

pattern). Field applications dictate that a good perforated base pipe design should have the following performance features: 1) It can be expanded without any cracking at any place in the pipe, 2) It can sustain desired tensile-load post expansion, 3) It has a good post-expansion collapse strength, 4) It should retain the above three performance criteria when material surfaces sustain mechanical damage during the expansion process. Thus, simulation for design of expandable perforated base pipe involves multiple analyses; i.e., simulation of expansion process, simulation of post expansion tensile test, and simulation of post expansion collapse or burst.

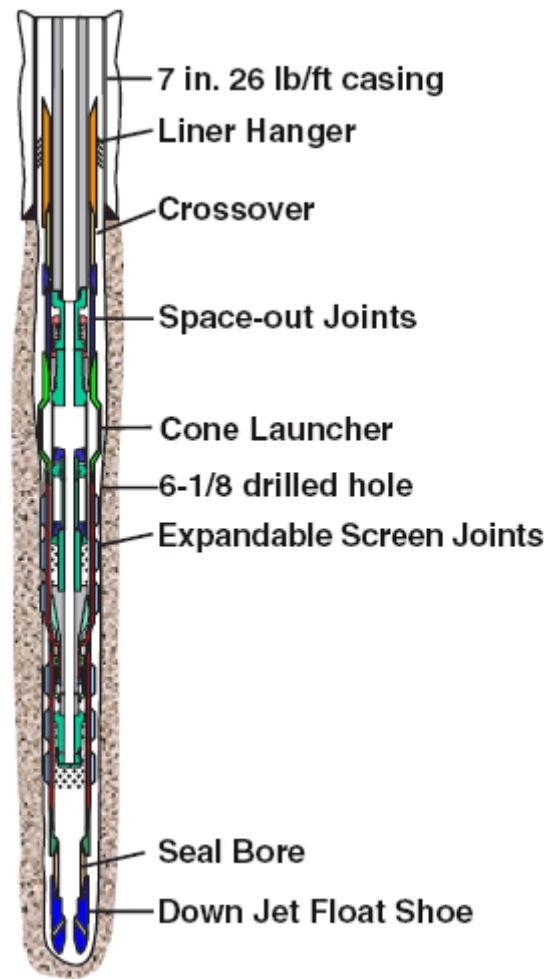
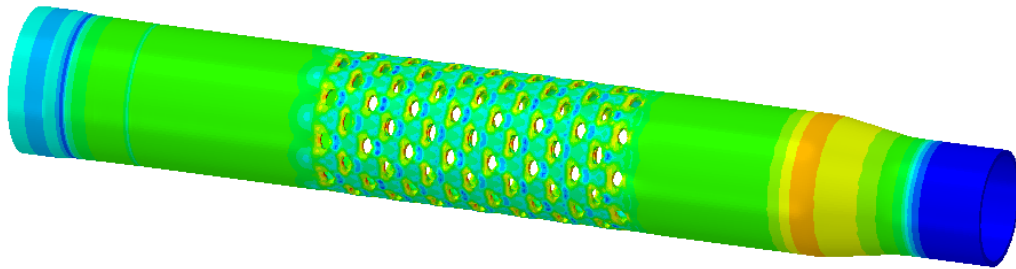


Figure 1 — An example of an Expandable System (Echols, 2002)

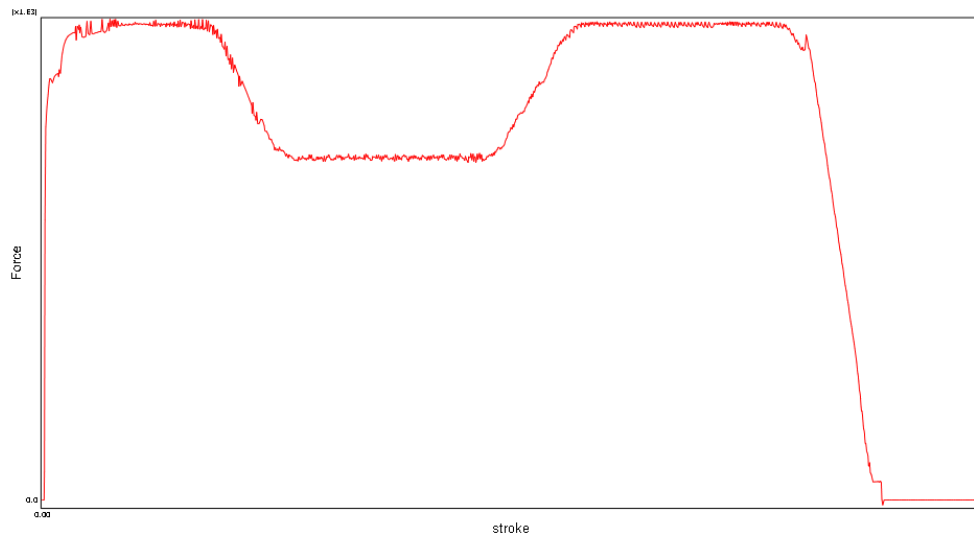
Due to the strong geometric and material nonlinearity involved, designing a high fidelity FEA model for expandable perforated base pipe is not easy. An explicit dynamics modeling technique has been used to avoid numerical difficulties (Jones, 2008). But, explicit dynamics can induce large numerical oscillations or very long run time when attempts are made to minimize artificial kinetic energy. The authors do not feel that explicit dynamics can predict satisfactorily the performance of expandable perforated base pipe. As a result, efficient and effective numerical procedures using Abaqus/standard for accurate prediction of the basepipe performance during expansion, post expansion tensile as well as post expansion collapse or burst, have been developed.

A typical model for expansion or tensile tests is a sector model accounting for symmetry in the geometry; contact between parts and friction are modeled as it is. An example of the simulation is shown in **Figure 2**.

Figure 2a shows the stress in the basepipe when the expansion cone is still inside the basepipe, and **Figure 2b** shows the expansion-force stroke curve. The valley in the curve corresponds to the perforated region of the pipe.



(a) An expanded base pipe



(b) Expansion Force vs. Stroke Curve

Figure 2 — An example of simulation of expansion of a perforated base pipe.

The tensile test simulation is a continuation of the expansion simulation, and typically, is the step following expansion. There are two types of tensile failure; i.e., fracture at holes or necking of the base pipe at the perforated region. **Figure 3** shows the tensile failure of an expanded base pipe due to necking in the perforated zone.

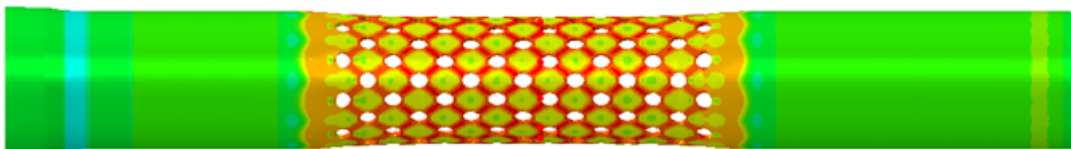


Figure 3 — An example of simulation of tensile failure of an expanded base pipe.

Post expansion burst of the base pipe can be simulated in the step following expansion although post expansion collapse is much more complex. A full 3D model is required for post expansion collapse analysis, since symmetry is lost in the collapse process. However, a straight forward full pipe simulation would lead to a prohibitively long simulation time, and thus, it would not be useful for design iterations. The authors developed a very efficient procedure (Zhong, 2007) for this type of analysis, conducting full 3d collapse analysis based on the sectorized model results, and thus, it was possible to perform this type of analysis for design iterations. An example of the collapse of an expanded based pipe is shown in **Figure 4**.

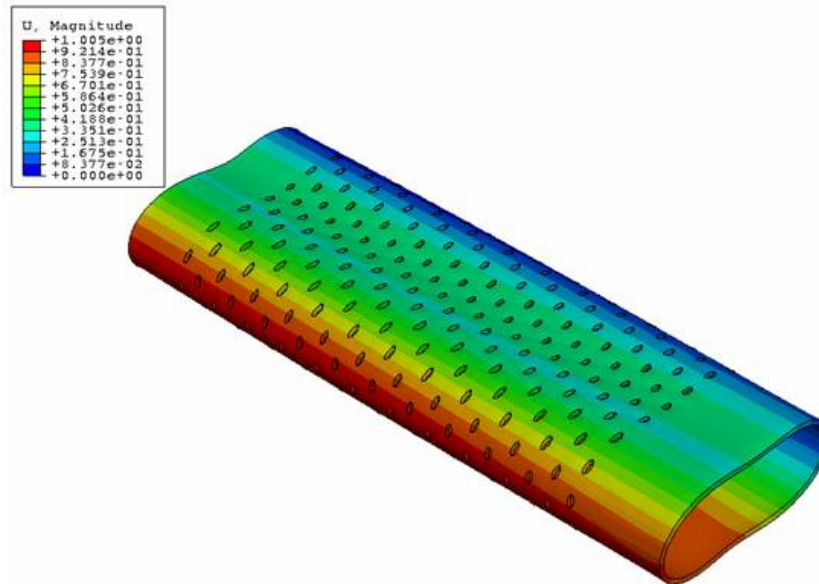


Figure 4 — An example of post expansion collapse of a basepipe (collapse mode is shown).

3. Optimization Technique

There are many approaches for design optimization. Two basic approaches with respect to how optimization is conducted are:

- A. *Response surface/surrogate model approach* – conduct enough FEA upfront, generate response surface (surrogate model) from FEA-predicted pipe response, and then, search for the optimum on the response surface.
- B. *Fully automated optimization* — optimization procedure will generate new design and evaluate and improve it automatically.

Considering the resource needed to automate the geometry generation and analysis procedure, the complexity of the analysis, as well as potential numerical issues in the numerical simulation process, it was determined that the response surface approach would be the best for the problem at hand.

A neural-network, ensemble-based surrogate model was constructed (Chen, 2007) for this project. First, candidate neural networks (NN) for limited simulation results were built in a typical way (see **Figure 5**). Then these NNs were assembled to form a neural network ensemble (NNE) (**Figure 6**) via a multi-objective genetic algorithm. The multiple objectives optimized for NNE construction included ensemble fidelity, complexity, and ambiguity. The advantage of NNE over NN is that 1) variance is reduced due to averaging over many solutions, 2) effort in generating individual solutions is retained, and 3), NNs, which determine the best ensemble size and member combination using genetic algorithm, are generated. The purpose of using NNE instead of NN is to make the surrogate model more robust. More details about NN and NNE construction will be discussed later in Section 4.2.

Once the surrogate model was constructed, optimum design was found via searching in the surrogate model – a response surface; millions of designs were evaluated in hours, accounting for multiple design objectives and constraints. Depending on the number of design parameters, for example, if the number is high, say 6 or more, the search process itself has to be optimized through genetic algorithm to efficiently find the feasible solutions. Thus, the genetic algorithm-based multi-objective optimization method discussed here has two-fold applications in both surrogate NNE construction and feasible solution searching. Due to the limitation on paper length, the details of this method will not be discussed here.

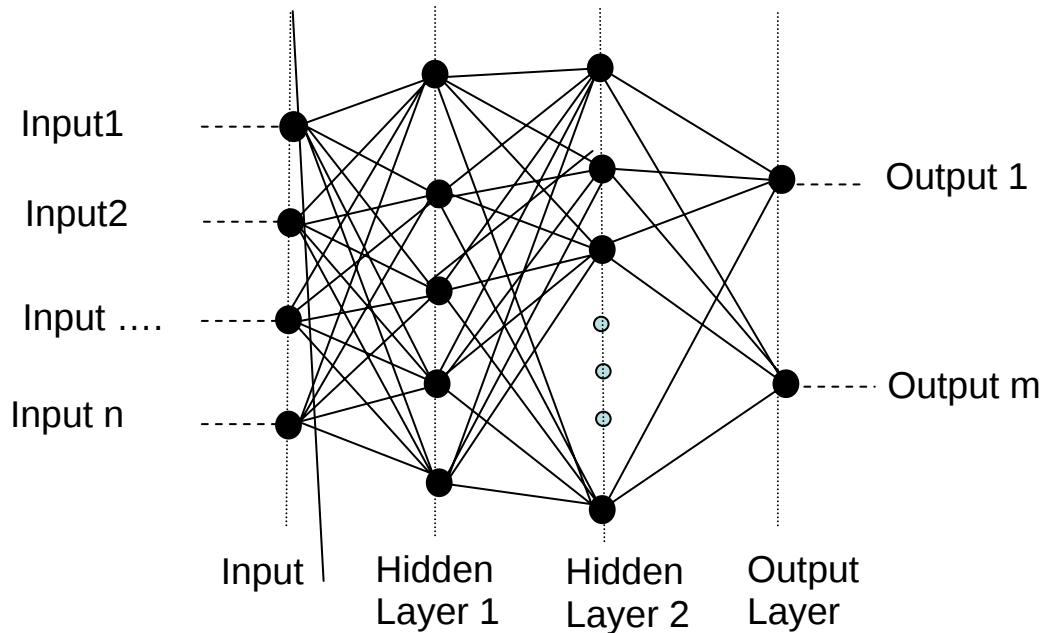


Figure 5 — Neural network representation of a design of experiment (DOE)

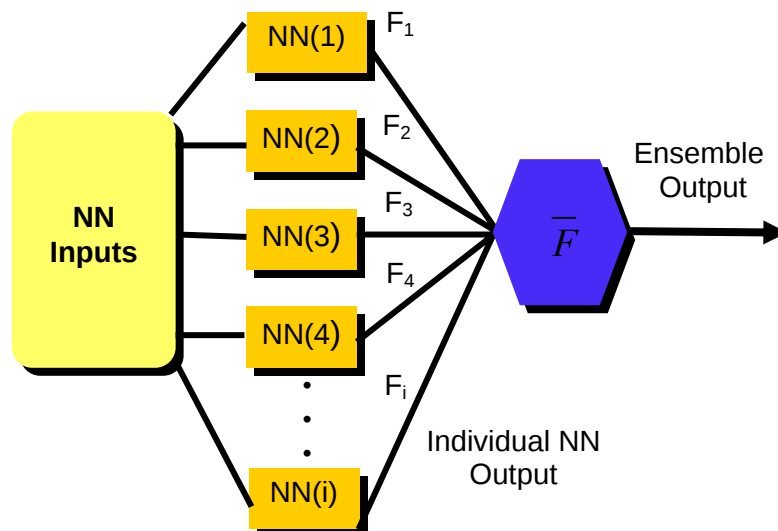


Figure 6 — Construction of Neural Network Ensemble

4. Design Optimization

Completion of numerical simulation is just the start of the optimization process. How to use numerical results for product performance evaluation is the key to designing optimization. In years of FEA applications, procedures and criteria have been established to determine whether a design can meet performance requirements, which include criteria for expandability, and for post expansion tensile/burst/collapse strength. Past FEA predictions have been validated repeatedly by physical tests with regards to expandability, post expansion tensile strength, and expansion force.

The goal of the design optimization is to increase the expansion rate of 7-in. perforated basepipe by 20% using current cone design and current material. The increase of the expansion rate will be achieved through hole-pattern optimization.

4.1 Definition of the design – parameters, constraint

Design parameters. It is assumed that the holes are placed regularly. There are 4 design parameters in this design, hole (generally being elliptic) sizes (a and b), hole spacing (s) and number of holes per row (N), as illustrated in **Figure 7**.

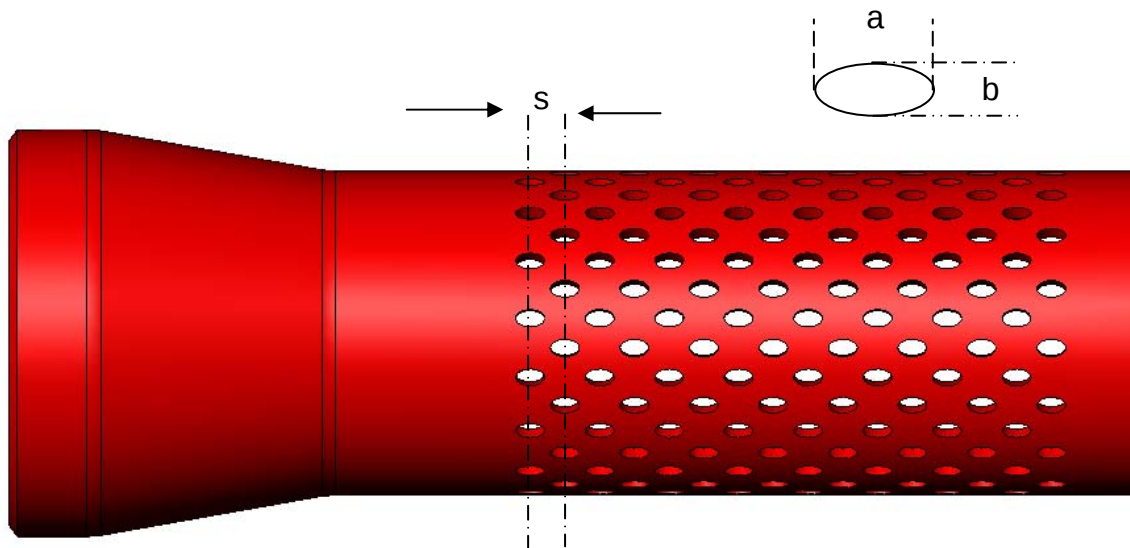


Figure 7 — Illustration of Design Parameters

Design constraints. Hole size (a,b) < 0.625-in., post expansion tensile strength > 400 kips, and collapse strength > 1400 psi. Other factors are drill capability of the hole and cost of drilling.

Design objective. The goal is to increase expansion rate by 20%. Numerically, this can be translated into minimizing plastic strain during expansion and maximizing post-expansion tensile strength.

4.2 Response surface and surrogate model construction (Chen, 2007)

Based on past experience and the authors' understanding of the mechanics of expandable basepipe performance, a design of experiment (DOE) of initial designs were analyzed first and used to construct a

candidate neural network. In this step, the total available input / output sample pairs were divided into two distinct groups. The first group, which contains more data points, ($N1$), is called the *primary group*. The group having the smaller number of points, ($N2$), is called the *secondary group*. The data in the primary group can be organized further into several sub-groups by applying 'leave- H -out' resampling, where H is the number of samples removed from the primary group. For simplicity, each sub-group may have the same number of data points ($N1-H$) with different excluded samples. Adequate training is applied to each individual network with appropriate control on training epochs and network complexity. The preferred pool size of candidate networks could be set to 32, 64 or 128, because these numbers can be conveniently represented by multi-bit binary integer codes for later ensemble construction using evolutionary selection algorithm.

One problem associated with sparse data modeling has been the existence of a large number of voids in the parameter space. The local ensemble having small member size and driven by a fixed objective function may interpret unseen data differently, if used alone. Therefore, global ensemble is needed to reduce the local ensemble-related variance and to improve the prediction over the whole parameter space. In this method, a global ensemble can be constructed by combining several local ensembles into a larger ensemble. To determine the best global ensemble members from the candidate local ensembles, the system developers still use the given primary and secondary data sets as an evaluation basis plus some other virtual validation measures in helping decision making. During the project, 62 designs were first analyzed, and simulation results were used to construct the surrogate model as described. Since the response surface has 6 dimensions (4 inputs, 2 outputs), only a cross section of the multi-dimensional space can be viewed in 3D. Representative cross sections of the response surfaces in 3D are shown in **Figures 8 and 9**. 52 DOE are put into the primary data set, and the other 10 DOE are put into secondary data set. Once NNs and NNEs are determined, the surrogate model is created (Chen, 2007).

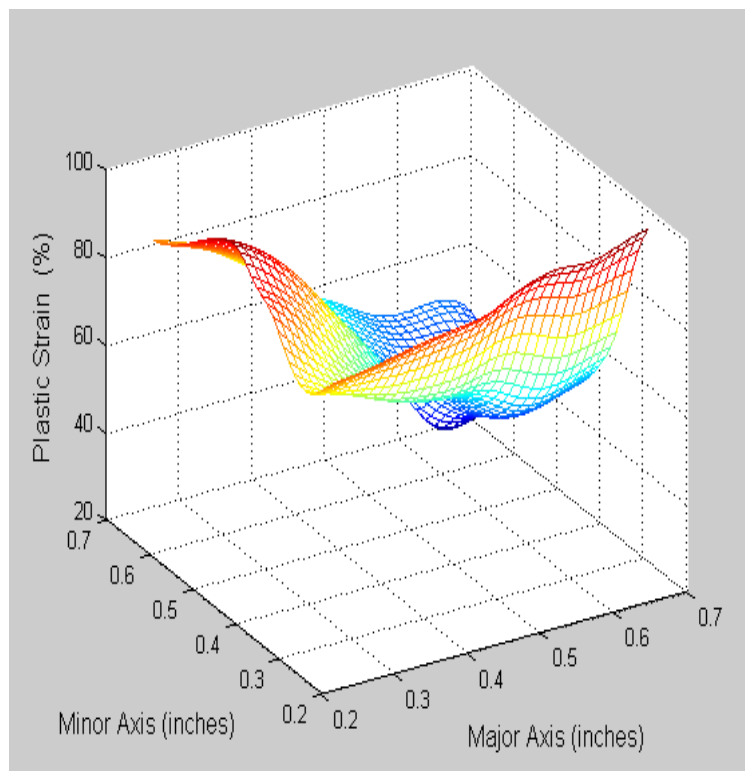


Figure 8 — 3D cross section of the response space – plastic strain vs. hole dimensions (s , N being constant)

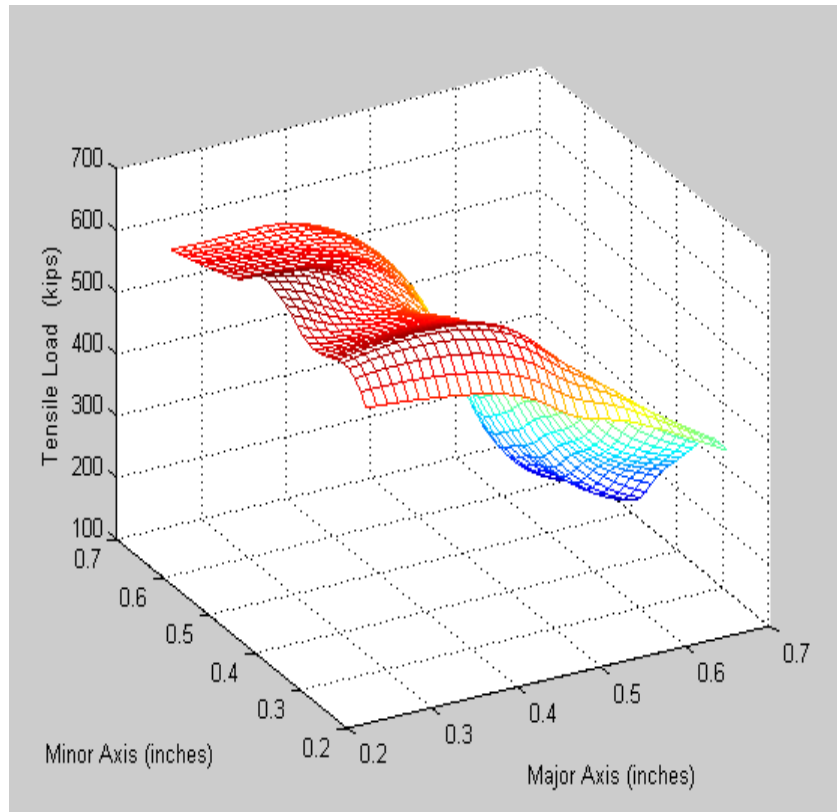


Figure 9 — 3D cross section of the response space – tensile strength vs. hole dimensions (s, N being constant)

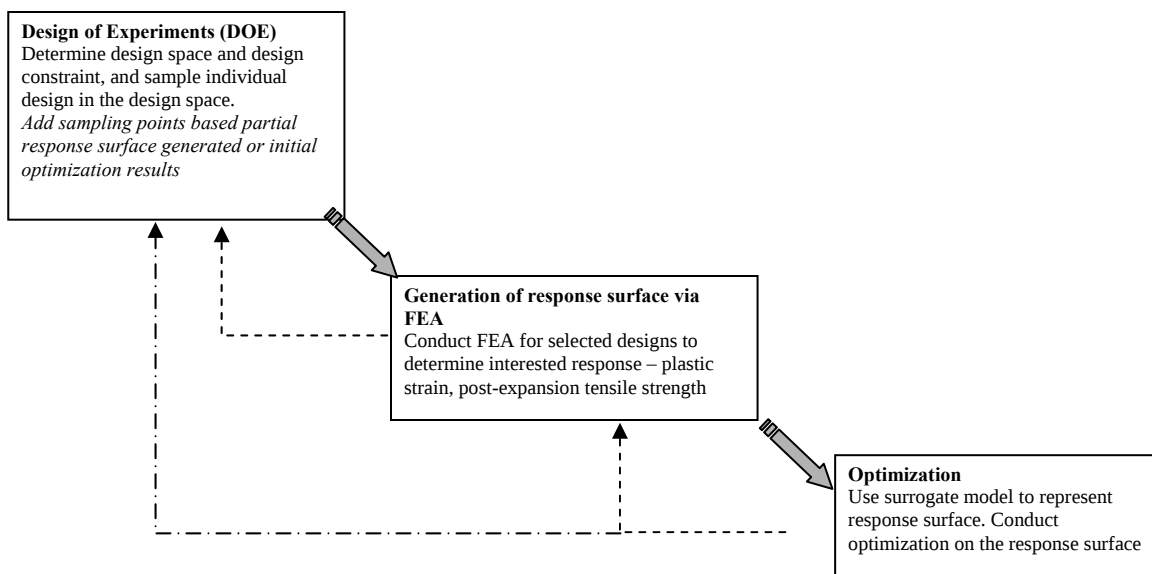


Figure 10 — Surrogate-Model-Based Design Optimization.

Validation of the surrogate model. Several better designs were found via the surrogate model. To check on the accuracy of the surrogate model, full FEA simulations were performed on the designs (s, a, b, N). The predictions from the surrogate model were compared to that from FEA predictions; plastic strain was within 15%, and tensile strength was within 5% for 4 designs checked.

4.3 Design optimization

Upon the construction of the surrogate model, better designs were found; additional FEAs were performed on the better designs selected per the surrogate models. The new FEA data were treated then as part of the DOE results for surrogate model refinement. This process, as illustrated in **Figure 10**, was iterated several times until no further improvement could be made to the surrogate model, and optimum designs were found from it. A group of designs yielded essentially the same low plastic strain and high tensile strength.

4.4 Optimum design and its robustness

One optimum design obtained has a post expansion maximum plastic strain at 50%, and tensile strength at 450 kips per FEA predictions. The tensile failure is in the form of local necking, see **Figure 11**.

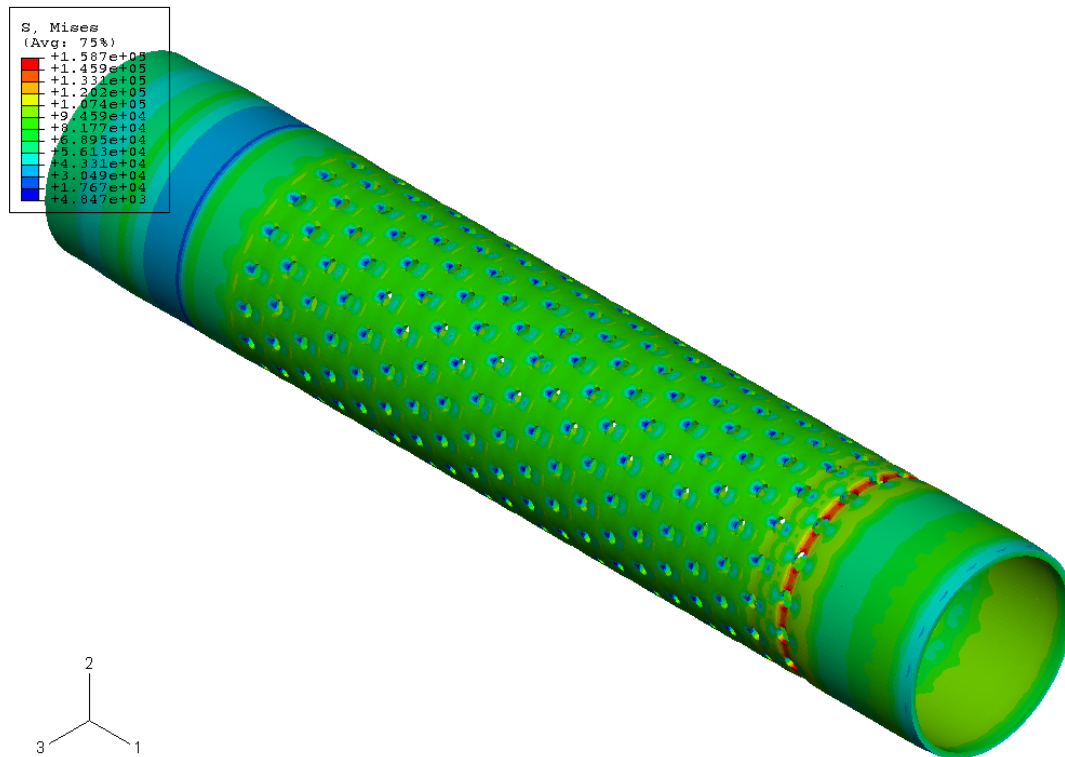


Figure 11 — Predicted tensile failure in the optimum design is 450 kips. Local necking occurred at 460 kips.

During the optimization process, the collapse strength of each design was not checked. A full 3d collapse analysis of the expanded optimum design (see Figure 4) shows that the design has a post expansion collapse strength ranging from 1307 psi to 1500 psi, depending on initial ovality of the base pipe.

Another issue of perforated basepipe robustness is its tolerance to initial defects (e.g. pipe damage or material defects) during the expansion process. A full 3D simulation of the optimum design with the worst

case scenario defect, an axial scratch at a first-row hole, was simulated. It is shown numerically per an empirical criterion that the design can tolerate the defect during the expansion process (**Figure 12**).

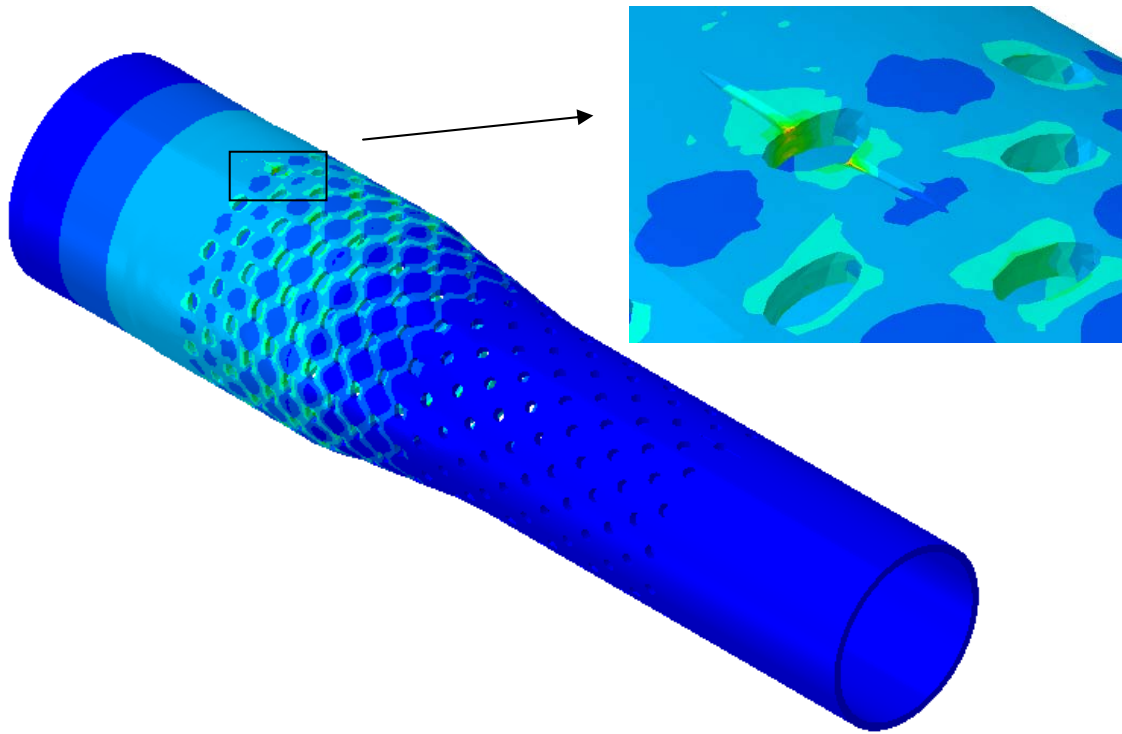


Figure 12 — Simulation of Scratch Resistance During Expansion

Several designs met the optimization requirement. A couple of them that were subjected to physical tests were expanded successfully at an expansion rate 20% higher than the current production expansion rate (See **Figure 13**) with robust scratch resistance (see **Figure 14**). In this test, the defect in the pipe is a machined groove representing pipe damage or material defect. The optimization was successful.

5. Concluding Remarks

The optimum designs obtained were restricted by the design space specified; i.e., the same perforations through the pipe and uniform spacing between holes. Better designs such as using multiple holes sizes, and/or varying hole spacing might be achieved by relaxing these restrictions. Manufacturability of the perforated base pipe and whether a different hole pattern can be drilled at a reasonable cost will be the major constraints for more exotic hole patterns. The optimization approach we developed through this work is highly effective and efficient. The authors have successfully applied the method to packer-element design optimization and expandable liner hanger optimization.

Design of a perforated base pipe that can be expanded at a high expansion rate is not difficult; a base pipe with high density holes or any other shapes of perforations can easily be expanded at a high expansion rate. That is why expansion of screen is never a problem and not a concern in designs. The problem with this type of design is that it has low tensile strength and low collapse strength. Since basepipe is the primary load carrier in sand screen systems, an expandable basepipe with good tensile strength and collapse strength is highly desirable.



Figure 13 — A perforated basepipe with optimized hole pattern was expanded successfully at a rate 20% higher than current production rate.



Figure 14 — A perforated basepipe with machined groove in the axial direction at the first row was expanded successfully at a rate 20% higher than current production rate.

6. References

1. Chen, D., Zhong, A., Gano, J., Hamid, S., De Jesus, O. and Stephenson, S. (2007), Construction of Surrogate Model Ensembles with Sparse Data, IEEE 2007 World Congress on Evolutionary Computation, September 2007, Singapore.
2. Echols R., Gano J., Shy, P., Tuckness, C., Zhang, H., and Campo D. (2002), Development and Testing of an Expandable Sand Screen and Expansion Tool, SPE73750, SPE International Symposium and Exhibition on Formation Damage Control, Lafayette, Louisiana, 20-21 February, 2002.
3. Jones, C., Watson, K. (2008), FEA modeling of Expandable Sand Screen, 2008 Abaqus USERS Conference, May 2008, Newport, RI., USA.
4. Zhong, A. (2007), Thread Connection Response to Critical Pressure, 2007 Abaqus USERS conference, May 2007, Paris, France.

7. Acknowledgements

The authors are grateful to the management of Halliburton for permission to publish this work.