Fluid Storage Structure Optimization Based on Fluid-Solid Coupling Analysis and Response Surface Method

Shigang Bao, Cuixiang Jiang, Junyan Ding and Wenwen Hu
College of Sciences, Wuhan University of Science and Technology, Wuhan, Hubei, 430065, China
Corresponding author’s e-mail: 835356630@qq.com

Abstract. The optimal structure parameters of the reservoir structure are investigated in this work. Based on bidirectional fluid-solid coupling analysis, a design of experiments (DOE) using the Latin hypercube sampling (LHS) is employed to build the response surface model of the reservoir structure. Response surface models have been shown to have good fitness. Multi-objective genetic algorithm (MOGA) is presented to search a precisely Pareto-optimal frontier for the problem. Numerical results show that the optimization method based on response surface model and response surface method can effectively overcome the limitations of experience dependence and obtain most efficient solutions for the problem. Through the optimization, the weight of the reservoir structure is reduced by 16.4% while the strength and stiffness of the structure has a little change.

1. Introduction
Reservoir structure is widely used in engineering. Its structure optimization is based on fluid-solid coupling analysis. However, the computational cost of fluid-solid coupling analysis is high, and the results of coupling impact are often affected by many structural design parameters. To grasp the impact of one of the design parameters on the target results requires a lot of repeated analysis and data comparison. Therefore, it is urgent to find an efficient optimization method to solve this kind of complex analysis. Based on the bidirectional fluid-solid coupling, the response surface of the liquid storage vessel is constructed by using the response surface model, which can intuitively understand the influence of design factors on the design objectives, and provide a set of optimization design methods for complex numerical analysis.

2. The liquid storage structure of two-way FSI analysis

2.1. Computational model
The research object of the cooling pool in this paper is simplified on the basis of existing terrestrial reinforced concrete cooling pool structure for spent fuel cooling of offshore nuclear power plants[1]. The cooling pool is 8 m long, 4.8 m wide and 6 m high. It weighs 66.679 T and has a total capacity of about 230400 L. It is welded by pool base, pool cover plate, pool longitudinal end plate, pool lateral end plate, longitudinal wave-proof plate, transverse wave-proof plate and other components. A U-shaped groove is arranged on the side of the wave-proof plate for the passage of grabs of spent fuel loaders and unloaders. Its structure is shown in figure 1. The finite element model of the reservoir structure is shown in figure 2, respectively. The fluid model is enclosed by the tank body plate. Therefore, the external structure of the water tank is removed and only internal wave-proof is retained.
The fluid domain mesh is divided by ICME software. The final fluid domain finite element model is shown in figure 3.

![Figure 1 Schematic diagram of water tank structure of cooling pool.](image1)

![Figure 2 Finite element model of cooling pool.](image2)

![Figure 3 Fluid domain model.](image3)

2.2. **The analysis results of FSI**

As there are no design codes and checking standards for cooling pools in marine environment at present, taking longitudinal impact as an example, the load size of cooling pool structure is (+1 g) impact, which is a feasibility study and analysis.

The maximum equivalent stress of cooling pool changes with time as shown in figure 4. The maximum stress appears on the wave-proof plate 3 in the 0-0.3s time interval and on the wave-proof plate 1 in the 0.3s-2.0s time interval. The maximum equivalent stresses of wave-proof plate 1 and wave-proof plate 3 reach their peak values in 0.6s.

According to the stress time history curve, the maximum stress and deformation nephogram of the cooling pool at 0.6 is output as shown in figure 5 and figure 6.

![Figure 4 Maximum stress time history curve.](image4)

![Figure 5 Maximum stress of the cooling pool.](image5)

![Figure 6 Maximum deformation of cooling pool.](image6)

2.3. **Design Variable Selection**

The structure of cooling water pool is mainly welded with stainless steel plate. The radius of the hole, the thickness of the wave-proof plate and the thickness of the pool body are selected as the design variables. The reason for choosing the aperture of the wave-proof plate is that the aperture of the wave-proof plate not only affects the flow and pressure distribution of the coolant in the cooling pool, but also relates to the shape of the wave-proof plate. In order to balance the stress on the box wall and the wave-proof plate under a certain aperture, which is the optimal aperture. This paper will focus on the impact strength, maximum deformation and weight of the cooling pool structure affected by the five variables of the aperture (R), the thickness of three types of wave-proof plates (FB1, FB2, FB3) and the thickness of the box (W). In order to improve the accuracy of response surface fitting, continuous design variables are used, considering the final roundness of steel plate manufacturing process according to the optimization results, and the values of each variable and the range of parameters are shown in table 1.
Table 1 Values and ranges of design variables

| Design variable | Initial value (mm) | Lower bound of variable (mm) | Upper bound of variable (mm) |
|-----------------|-------------------|-----------------------------|-----------------------------|
| R               | 600               | 300                         | 620                         |
| FB1             | 10                | 8                           | 12                          |
| FB2             | 10                | 8                           | 12                          |
| FB3             | 10                | 8                           | 12                          |
| W               | 30                | 12                          | 32                          |

3. Constructing response surface

3.1. Design of experiment (DOE)

In order to construct an approximate model with as few experimental times as possible and valid experimental datum, Latin Hypercube Sampling (LHS) [2] is used to generate experimental design points. The principle is that in n-dimensional space, each coordinate interval \([x_{ij}^m, x_{ij}^m], k \in [1, n]\) is evenly divided into m intervals. Random selection of M points ensures that each horizontal value of a factor is studied once, that is to say, a Latin hypercube design with n-dimensional space and m samples is constructed. Compared with the full factor design, it can obtain more factor level combinations with fewer experimental times and have better coverage of the whole adoption space [3].

3.2. Response surface method

Response surface method (RSM) [4] is a method for constructing approximate models. Through the limited experimental design of the set of sample points in the specified design space, the design space is fitted by appropriate iteration strategy, so that the output variables (system response) are approximated globally instead of the real response surface, and the implicit function is expressed by a polynomial with explicit expression [5].

For the accuracy of fitting surface, the determination coefficient \(R^2\) is often used to test the accuracy of fitting surface. The closer the \(R^2\) value is to 1, the higher the fitting degree of response surface model is, the more the relationship between objective function and design variables can be reflected. However, sometimes this condition does not necessarily hold. For example, adding some meaningless statistics in the model can also lead to the increase of \(R^2\). Therefore, it is necessary to introduce root mean square error \(R_{RMSE}^2\). Together, they can well judge the validity of the response surface model. The calculation formula is as follows:

\[
R^2 = 1 - \frac{\sum_{i=1}^{m} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{m} (y_i - \bar{y})^2}
\]

(1)

\[
R_{RMSE} = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2}
\]

(2)

Where \(y_i\) is the response value corresponding to the first sample point, and \(\hat{y}_i\) is the predicted response value obtained by response surface model.

Formula 1 and 2 are used to analyze the variance of the response surface model. The results are shown in table 2. It can be seen that the determinant \(R^2\) of each objective function is larger than the engineering standard of 0.9 or more and is close to 1, and the root mean square error \(R_{RMSE}^2\) is
relatively small. According to table 2, it can be judged that the fitting degree of response surface model is relatively high, and the real response value of each design variable can be predicted comparatively.

| Objective function         | Coefficient of determination | Root-mean-square error |
|----------------------------|-------------------------------|------------------------|
| Maximum equivalent stress  | 0.986625632                  | 0.075689523            |
| Maximum deformation        | 0.995632458                  | 0.034568525            |
| quality                    | 0.999836542                  | 0.000031623            |
| Ideal value                | 1                             | 0                      |

4. Structure optimization of cooling pool

4.1. Multi-objective optimization based on genetic algorithm
The multi-objective non-dominated sorting genetic algorithm (NSGA-II) [6] based on elite strategy in multi-objective genetic algorithm (MOGA) is used to optimize the algorithm, which is improved by NSGA. NSGA-II uses a fast non-dominant sorting algorithm to merge the parent population with the offspring population, thus retaining all the best individuals. Elite strategy is introduced to ensure that some excellent population individuals will not be discarded in the evolutionary process, thus improving the accuracy of the optimization results. Crowding degree is used as a comparison standard between individuals in the population, so that the individuals in the quasi-Pareto domain can be evenly extended to the whole Pareto domain, demonstrating the diversity of the population.

4.2. Pareto front
Pareto [7] solution is also called non-dominant solution: when there are multiple objectives, one solution is the best in one goal and the worst in other goals because of the conflict and incomparability between objectives. While improving any objective function, these solutions will inevitably weaken at least one other objective function, which is called non-dominant solution or Pareto solution. The set of optimal solutions of a set of objective functions is called Pareto optimal set, and the surface formed by the optimal set in space is called Pareto frontier. The frontier of Pareto solution obtained is shown in figure 7. All points in the graph are Pareto boundary points.

4.3. Optimum design results and verification
After optimization, five Pareto optimal solution levels are obtained as shown in table 3. Considering the design objectives of cooling pool weight, deformation and stress, taking candidate point 4 as an example, the data are rounded and used as the optimal design point. The two-fluid-solid coupling and analysis of cooling pool under the design parameters are carried out. The comparison of data before and after optimization of cooling pool is shown in table 4.
Table 3 Candidates for Pareto Solutions

| Candidate point | R(mm) | FB1(mm) | FB2 (mm) | FB3 (mm) | W(mm) | Maximum equivalent stress / MPa | Maximum deformation / mm | Mass/ kg |
|-----------------|-------|---------|----------|----------|-------|---------------------------------|--------------------------|----------|
| 1               | 554.50| 8.05    | 8.07     | 8.83     | 22.41 | 122.07                          | 6.47                     | 51.02    |
| 2               | 441.60| 8.58    | 8.13     | 10.03    | 24.6  | 100.21                          | 5.10                     | 56.12    |
| 3               | 514.18| 8.03    | 8.23     | 9.57     | 25.37 | 97.98                           | 4.74                     | 56.89    |
| 4               | 413.22| 8.47    | 8.10     | 9.47     | 24.35 | 103.42                          | 5.23                     | 55.55    |
| 5               | 316.18| 9.25    | 8.15     | 10.34    | 23.95 | 99.59                           | 5.45                     | 55.77    |

Table 4 Data comparison before and after optimization

| Parameter                  | Before optimization | Optimized predicted calculated after rounding | Maximum equivalent stress (MPa) | Maximum deformation (mm) | Mass(kg) |
|----------------------------|---------------------|-----------------------------------------------|--------------------------------|--------------------------|----------|
| R(mm)                      | 600.00              | 316.18                                        | 105.50                         | 3.40                     | 66.68    |
| FB1(mm)                    | 10.00               | 9.25                                          | 99.59                          | 5.45                     | 55.77    |
| FB2 (mm)                   | 10.00               | 8.15                                          | 99.59                          | 5.45                     | 55.77    |
| FB3 (mm)                   | 10.00               | 10.34                                         | 104.50                         | 5.43                     | 55.80    |
| W(mm)                      | 30.00               | 24.00                                         |                                |                          |          |

Because of the manufacturing process and other reasons, the optimal solution data need to be rounded to facilitate processing and manufacturing. After rounding the cooling pool parameters, the bidirectional fluid-solid coupling calculation is carried out. The overall deformation and equivalent stress distribution of the cooling pool are shown in figure 8 and figure 9 respectively. The maximum stress position is transferred from the top of the wave-proof board to the longitudinal end plate. The maximum stress of longitudinal endplate is shown in figure 10.

5. Conclusion
The response surface approximation model of the reservoir structure was constructed based on fluid-solid coupling analysis and response surface method with limited experimental design (DOE) sample points. The Paerto optimal solution frontier of the optimization design of reservoir structure parameters was obtained by multi-objective genetic algorithm. While controlling the structure of the cooling pool not exceeding the allowable strength of the material, the weight of the structure was reduced by 16.4%, and the increment of maximum equivalent stress and maximum deformation was relatively small. The results show that the optimization method of reservoir structure based on response surface model and response surface method can effectively overcome the shortcomings of repeatability and experience dependence in the design of overall performance scheme of reservoir structure. It can provide sufficient basis for decision makers to weigh objectives and provide design reference and solutions for other complex model design optimization problems.

References
[1] Zhang, Y., Buongiorno, J., Golay, M., & Todreas, N. 2018. Safety analysis of a 300-mw(electric) offshore floating nuclear power plant in marine environment. Nuclear Technology, 1-17.
[2] Zolan, A. J., Hasenbein, J. J., & Morton, D. P. 2018. Optimizing the design of a latin hypercube sampling estimator. *Simulation Conference*. IEEE.

[3] Helton, J. C., & Davis, F. J. 2003. Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems. *Reliability Engineering & System Safety*, 81(1), 23-69.

[4] Beal, V. E., Erasenthiran, P., Hopkinson, N., Dickens, P., & Ahrens, C. H. 2006. Optimisation of processing parameters in laser fused h13/cu materials using response surface method (rsm). *Journal of Materials Processing Tech*, 174(1), 145-154.

[5] Wang, G. G. 2003. Adaptive response surface method using inherited latin hypercube design points. *Journal of Mechanical Design*, 125(2), 210-220.

[6] Bekele, E. G., & Nicklow, J. W. (2007). Multi-objective automatic calibration of swat using nsga-ii. *Journal of Hydrology*, 341(3), 165-176.

[7] Andersson, J., & Wallace, D. 2002. Pareto optimization using the struggle genetic crowding algorithm. *Engineering Optimization*, 34(6), 623-643.