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Flexible Riser Configuration Design for Extremely Shallow Water With Surrogate-Model-Based Optimization

The aim of this paper is to study the optimization design of a steep wave configuration based on a surrogate model for an extremely shallow water application of a flexible riser. As the traditional technique of riser configuration design is rather time-consuming and exhaustive due to the nonlinear time domain analysis and large quantities of load cases, it will be challenging when engineers address an extreme design, such as the configuration design in the case of extremely shallow water. To avoid expensive simulations, surrogate models are constructed in this paper with the Kriging model and radial basis function (RBF) networks by using the samples obtained by optimal Latin hypercubic sampling (LHS) and time domain analysis in a specified design space. The RBF model is found to be easier to construct and to show better accuracy compared with the Kriging model according to the numerical simulations in this work. On the basis of the RBF model, a hybrid optimization is performed to find the minimum curvature design with corresponding engineering constraints. In addition, an optimized design is found to meet all of the design criteria with high accuracy and efficiency, even though all of the samples associated with construction of the surrogate model fail to meet the curvature criterion. Thus, the technique developed in this paper provides a novel method for riser configuration design under extreme conditions. [DOI: 10.1115/1.4033491]

1 Introduction

Riser configuration design is typically a time-consuming and exhaustive task due to the requirements of nonlinear simulations in the time domain and a large number of load cases and parametric studies. More specifically, global analysis must be performed throughout the whole stage to obtain the displacement and force resultants that are caused by internal and external loads. In addition, the nonlinear time domain method is usually required in the global analysis because of the many load and structure nonlinearities, such as hydrodynamic loads, nonlinear material or geometry effects, and seafloor contacts [1,2]. Typically, hundreds of load cases derived from the combinations of waves, currents, and floater motions should be analyzed, and sensitivity studies are also required for some environmental parameters to build a proper load matrix [2]. Based on the above techniques, parametric studies on riser configurations are needed to find a feasible configuration [3–6]. Therefore, the number of design variables determines the difficulty of the task of designing riser configurations, e.g., a lazy wave design with three design variables may result in thousands of geometric configurations that must be analyzed [3]. Obviously, by means of the traditional design techniques mentioned above, it would be more difficult when the design meets extreme conditions, such as extremely shallow water (depth < 50 m), ultradeep water (depth > 1500 m), or severe sea states, because the feasible design domains are usually too narrow to find a feasible design in extreme cases. Even worse, more severe challenges may be faced when engineers address an urgent design, such as in the case of an oil-spill incident combined with extreme conditions.

Most of the previous studies have focused on the design of riser configurations in deep water. However, the challenges are certainly not reduced and could be very different when the design is performed in extremely shallow water [7]. The challenges may be derived from strong currents, large waves, variations in product density, marine growth, and so on. In particular, typical configurations, including a lazy/steep-S and lazy/steep wave, will approximate or exceed their compliancy capabilities to the vessel motions in extremely shallow water. As a result, some new configurations have been developed for flexible risers in shallow water applications, such as the multiwave [7], tensioning mechanism system [8], and weight added wave [9] configurations. However, the application of new configurations may be involved with other problems, e.g., a longer design cycle, more expensive qualification, and higher risks. Meanwhile, the potential of the typical configurations mentioned above tends to not be fully utilized due to the time-consuming traditional design methodology. Therefore, the purpose of this work is to exploit the potential of the typical configurations, especially the steep wave riser configuration, to efficiently cope with a flexible riser configuration design in extremely shallow water. In addition, the optimization technique is introduced in this work to accelerate the design process and obtain better performances of the flexible riser.

Optimization of riser configurations was first introduced by Larsen, who used a genetic algorithm (GA) in a static analysis program for a steel catenary riser (SCR) configuration design [10]. Later, similar works were performed to develop the GA [11–14] and other algorithms for the riser configuration design, such as an artificial immune system and particle swarm optimization [15–17]. However, all of these works are based on static analysis because the time domain dynamic analysis for risers is too

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expensive to be performed during the configuration optimization. To consider the dynamic behavior of risers during the optimization process, Tanaka and de Arruda Martins performed optimization with frequency domain dynamic analysis [18,19]. Martins et al. performed time domain simulation in a computer cluster with 1376 cores in total, with only four load cases considered [20]. In summary, the optimization techniques developed to date are not adequate for a practical riser configuration design.

Surrogate models, also known as metamodels, were initially developed as surrogates of the expensive simulation processes to improve the overall computation efficiency [21]. Surrogate models have recently been introduced into ocean engineering design [22–29]. The main purpose of using these techniques in riser configuration design is to represent the dynamic responses of risers by means of a mathematical approximation model instead of performing the time domain analysis, so that the design or optimization is very efficient. Guarize et al. trained neural networks to replace the time domain analysis of risers and anchor lines; this approach followed the "surrogate" idea [30]. Yang and Zheng applied the surrogate model in the optimization design of deep water SCR optimization design using the Kriging model [31]. However, the use of surrogate models is still not adequate in riser configuration design and optimization. As a result, additional attempts are required to verify its efficiency and reliability. In the future, this technique may become a powerful methodology for riser configuration design; its potential is demonstrated in this manuscript.

In this work, surrogate-model-based optimization is performed to implement a riser configuration design in extremely shallow water. The engineering background is an oil spill from a sea floor leak in shallow water with a depth of 27 m. The solution for this incident is to collect the spilled oil from the sea floor and transport it to the sea surface using a system that is like a catenary anchor leg mooring system, as shown in Fig. 1. A riser should be designed to connect the seabed oil collection device to the surface container. Obviously, it is difficult to find a feasible solution for the riser configuration in such an extremely shallow water application with very limited time. The steep wave is selected to be the riser configuration for this system. However, many attempts to achieve a feasible configuration design for the engineering task have failed because of the very narrow feasible domain in this extreme application. In the practical design process, the dynamic curvatures are found to be too large under the extreme load conditions, occurring at the hog bend of the configurations that cannot be eliminated by bend stiffeners.

Therefore, we develop an optimization model that seeks the configuration with minimum curvature. The curvature of interest is the maximum dynamic value obtained from the hog bend of each configuration. Four key geometric parameters are taken as the design variables, and the ranges of the responses are used as the constraints including tension, hang-off angle, seabed clearance, and length redundancy. The surrogate models representing the relationship between the design variables and dynamic responses are constructed using the Kriging model and RBF networks, based on samples from optimal LHS processes and time domain analyses, respectively. The RBF model shows better accuracy than the Kriging model based on the model validation in this research. Therefore, a hybrid optimization based on the RBF model is performed combined with the multi-island GA (MIGA) [32] and nonlinear programing by quadratic Lagrangian (NLPQL) [33]. Finally, the optimization result is verified by time domain analysis, in which we determine that the accuracy and efficiency of the optimization model are both satisfactory.

2 Problem Description

A steep wave configuration is achieved by a hanging pipe with several buoyancy modules distributed along its intermediate segment and a fixed touch-down point. Generally, the design of a steep wave configuration involves the length design of each segment of the riser, the fixed position on the seabed, and the buoyancy modules including the net buoyancy, number, and distributions. Seven of the abovementioned design variables are needed to form a tremendous design space, making it difficult to explore an optimum design in practice. Even using some mathematical programing, it is still difficult to consider all of the design variables at one time. Therefore, simplification of the steep wave design is necessary. Assuming that the buoyancy modules are predetermined and that the riser segment where the buoyancy modules are distributed is equivalent to a uniform pipe segment according to the overall weight and buoyancy, the number of design variables is reduced to four, as shown in Fig. 2. These design variables are upper catenary length L_1, buoyancy segment length L_2, lower catenary length L_3, and the horizontal distance between the hang-off point and the touch-down point P.

The large number of load cases is another challenging problem for the design of riser configurations, which has not been satisfactorily solved in most of the previous works. One of the important reasons is that the critical failure modes in some load cases may differ from other load cases, e.g., the main failure model of risers at a far position is tensile failure, whereas it is overbending or clashing at a near position. Nevertheless, it is usually found that only a few cases are critical for the design of the riser configuration in the preliminary stage, which makes the optimization design of the riser configuration feasible. In the above system, the critical load case for the steep wave riser is the near position with the wave and current collinear, where the riser suffers a large bending moment and faces a great risk of interference with the seabed. Based on our design experiences, other cases may be taken into account by means of providing redundancy in the length and margins for the constraints during the optimization.

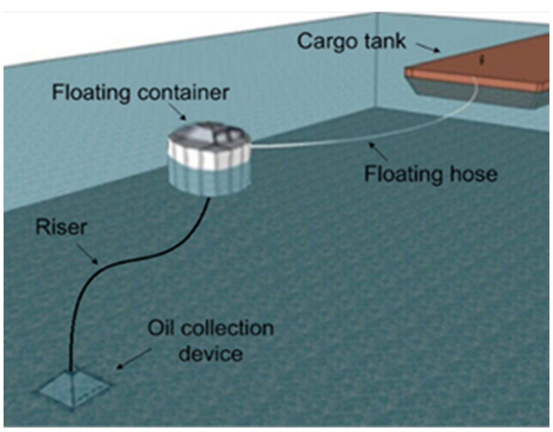

Fig. 1 Solution for the oil-spill incident

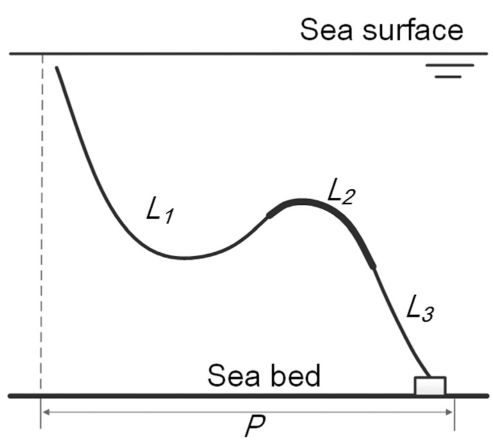

Fig. 2 Design variables for the steep wave configuration

Therefore, the steep wave model is built using the parameters described in Table 1. The riser is hinged at both ends in the analysis model because two bend stiffeners will be designed to prevent possible overbending at the ends.

3 Optimization Model

As previously described, the design of a steep wave configuration for risers is simplified and can be converted into an optimization problem involving the search for the configuration with the minimum dynamic curvature under the constraints of other criteria. The target curvature C is required to be less than 0.25 rad/m, as derived from the minimum bending radius (MBR) criterion of the given flexible pipe. Next, the ranges of the design variables, constraints, and optimization formulae are specified.

3.1 Range of Design Variables. Considering the geometry of the steep wave configuration, the following ranges for the design variables are adopted preliminarily based on engineering specifications and experience:

$$\begin{cases} 15\ \text{m} \le L_1 \le 30\ \text{m} \\ 8\ \text{m} \le L_2 \le 12\ \text{m} \\ 3\ \text{m} \le L_3 \le 12\ \text{m} \\ 10\ \text{m} \le P \le 40\ \text{m} \end{cases} \tag{1}$$

3.2 Constraints. All of the design criteria, except the maximum curvature criterion (the optimization objective), are taken as constraints. The constraint range setting may include the consideration of some margins to include the numerical errors and some uncertainties of load cases. Four constraints and their ranges are considered as follows:

- *Maximum dynamic tension* T: The dynamic tension range can be determined from a testing calculation.
- *Maximum hang-off angle* θ: This constraint is based on the hinged model of the riser ends; the range is assumed to not interfere with the floater, and no overbending is assumed to occur if a bend stiffener is added.
- *Minimum clearance between the riser sag bend and seabed* d: The minimum clearance is set to be greater than a given value to avoid interference with the seabed and is set to be less than a given value to maintain a proper distance from the sea surface.
- *Length redundancy* ΔL. This parameter is introduced to ensure that the total length of the risers is sufficient; the length redundancy can be expressed as

$$\Delta L = L_1 + L_2 + L_3 - \sqrt{(P + 2\cdot \text{offset})^2 + H_{\max}^2} \tag{2}$$

where $H_{\max}$ is the maximum distance between the riser hang-off point and the seabed in the extreme condition, and offset is the floater offset.

Table 1 Parameters for the configuration design

Parameter	Value
Water depth (m)	27
Outside diameter of L_1 and L_3 (mm)	180
Weight of L_1 and L_3 in air (kg/m)	37
Outside diameter of L_2 (mm)	418
Weight of L_2 in air (kg/m)	50
Floater offset (m)	5
Floater draft (m)	3
Maximum wave height (m)	8.8
Wave period (s)	8.6
Surface current speed (m/s)	1

Therefore, the ranges of these constraints are set as follows after consideration of the above factors and based on some engineering experience:

$$\begin{cases} 0\,\text{kN} \le T \le 30\ \text{kN} \\ 0\,\text{deg} \le \theta \le 75\,\text{deg} \\ 2\ \text{m} \le d \le 12\ \text{m} \\ 1\ \text{m} \le \Delta L \le 20\ \text{m} \end{cases} \tag{3}$$

3.3 Optimization Formulation. Hence, the optimization model of the steep wave configuration design can be stated as follows:

$$\begin{aligned} &\text{To find } L_1, L_2, L_3, P \\ &\min. C(L_1, L_2, L_3, P) \\ &\text{s.t.} \begin{cases} T_L \le T \le T_U \\ \theta_L \le \theta \le \theta_U \\ d_L \le d \le d_U \\ \Delta L_L \le \Delta L \le \Delta L_U \end{cases} \end{aligned} \tag{4}$$

where L_1, L_2, L_3, P, C, T, θ, d, and ΔL are defined as above. The subscripts L and U denote the lower and upper bounds of the constraints, respectively, and their values are also specified in Eq. (3).

4 Construction of the Surrogate Model

As the time domain simulations of the dynamic responses are too expensive to be performed directly during the optimization of the riser configurations, a surrogate model is utilized to simulate the design variables/responses relationships based on some sample points. The basic formulation of the surrogate model can be expressed as follows:

$$f_p(\mathbf{x}) = \hat{f}(\mathbf{x}) + \varepsilon(\mathbf{x}) \tag{5}$$

where $\mathbf{f_p}$ is the true response at design point $\mathbf{x}$, $\hat{\mathbf{f}}$ is the model estimation, and $\varepsilon(\mathbf{x})$ is the error in the surrogate model.

There are several approaches that can be used to construct the surrogate model, such as polynomial regression, the Kriging model, and RBF. Considering that the polynomial model is less accurate for highly nonlinear problems [21], we use the Kriging and RBF models in this work.

4.1 Kriging Model. The Kriging model was initially developed to determine the true ore-grade distributions based on sample ore grade in the 1950s [34]. It is useful in predicting temporally and spatially correlated data. The main idea of the Kriging model is to use its basic formulation to estimate the value of a response at some unsampled location. The ordinary estimating deterministic function of the Kriging model can be stated as [35]

$$f(\mathbf{x}) = \mu + \varepsilon(\mathbf{x}), \quad E(\varepsilon) = 0 \tag{6a}$$

$$\operatorname{cov}(\varepsilon(\mathbf{x}^{(i)}), \quad \varepsilon(\mathbf{x}^{(j)})) \ne 0, \quad \forall i, j \tag{6b}$$

where μ is the mean of the response at sampled design points, and ε is the error with zero expected value. A correlation function of a generalized distance is used between the sample data points, which determines the accuracy of the model.

Let $\hat{f}(\mathbf{x})$ be an approximation model. When the mean squared error between $f(\mathbf{x})$ and $\hat{f}(\mathbf{x})$ is minimized, $\hat{f}(\mathbf{x})$ becomes

$$\hat{f}(\mathbf{x}) = \hat{\mu} + \mathbf{r}^{\mathrm{T}}(\mathbf{x})\mathbf{R}^{-1}(\mathbf{f} - \hat{\mu}\mathbf{i}) \tag{7}$$

where $\hat{\mu}$ is the estimated value of μ, $\mathbf{R}^{-1}$ is the inverse of correlation matrix $\mathbf{R}$, $\mathbf{r}$ is the correlation vector, $\mathbf{f}$ is the observed data with n sample data, and $\mathbf{i}$ is the vector with n components of 1. For the possible correlation structure of $\mathbf{R}$, interested reader may refer to Refs. [35,36].

4.2 RBF Model. The RBF approximation is a type of neural network employing one hidden layer of radial units and an output layer of linear units that is capable of a universal approximation [37], as shown in Fig. 3. And the basic formulation is expressed as follows:

$$f(\mathbf{x}) = \sum_{i=1}^{N} w_i h_i(\mathbf{x}) + \varepsilon_i \tag{8}$$

where w is the coefficients of the linear combinations, $h_i(\mathbf{x})$ is the basis functions, ε_i is the independent errors with variance σ^2, and N is the number of the RBFs. There are many forms of function for $h_i(\mathbf{x})$, including Gaussian, reflected sigmoidal, inverse multiquadrics, and power spline. Then, the RBF model can be expressed as $\mathbf{F} = \mathbf{H}\boldsymbol{w}$, where $\mathbf{H}$ is a $N \times M$ matrix of RBFs $h_i(\mathbf{x})$, and the coefficients $\boldsymbol{w}$ are given by $\boldsymbol{w} = \mathbf{H}^{-1}\mathbf{F}$, which is calculated from the training samples.

Generally, a surrogate model can be constructed by four key steps: design of the experiment, simulation of selected samples, construction of the model, and model validation.

4.3 Design of the Experiment. To obtain a highly accurate surrogate model, the optimal LHS approach is applied. In addition, 300 sample points are obtained preliminarily. The samples from the optimal LHS cover the design space well without replication and are distributed uniformly and randomly [38,39]. Large quantities of these samples do not satisfy the length redundancy constraint and were removed at this stage. Finally, 152 sample points remained for the subsequent simulation. A three-dimensional distribution can be observed from Fig. 4, and other combinations of the four design variables are distributed similarly and are omitted here.

4.4 Simulation of the Selected Samples. Numerical simulation is performed using the batch process of Orcaflex [40] on the samples that were previously obtained. The regular wave approach [1,2] is used to reduce the computation cost. The total time for running the 152 samples is less than 6 hrs with a 4-core Intel i5 central processing unit (CPU) computer. The following responses are obtained to construct the surrogate model: the maximum dynamic curvature, tension, hang-off angle, and minimum clearance between the sag bend.

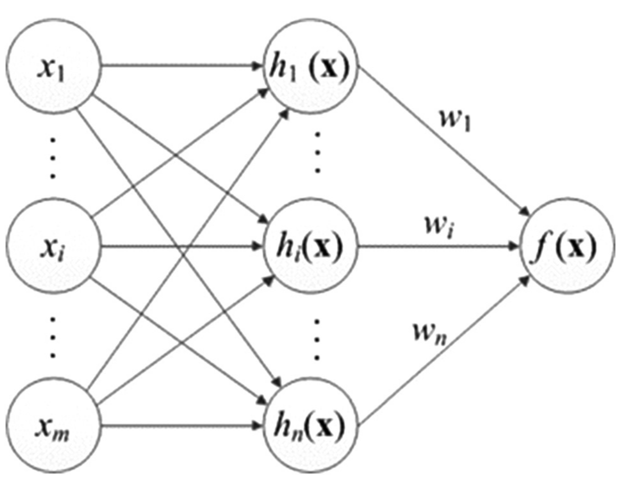

Fig. 3 Traditional RBF networks

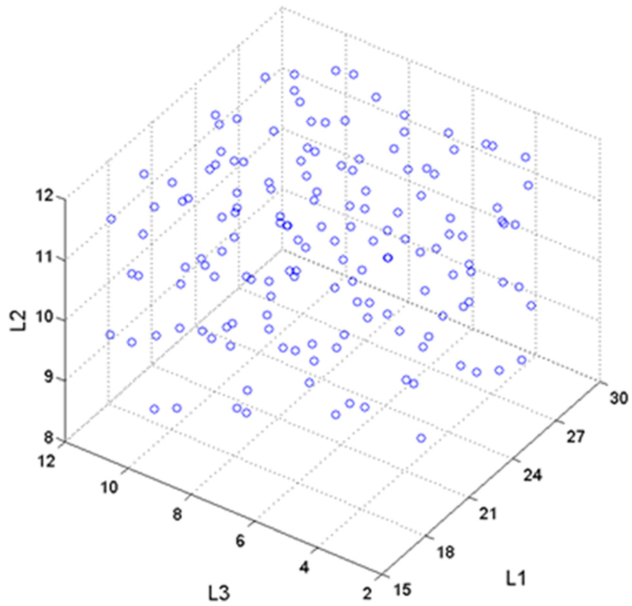

Fig. 4 Selected samples from the optimal LHS

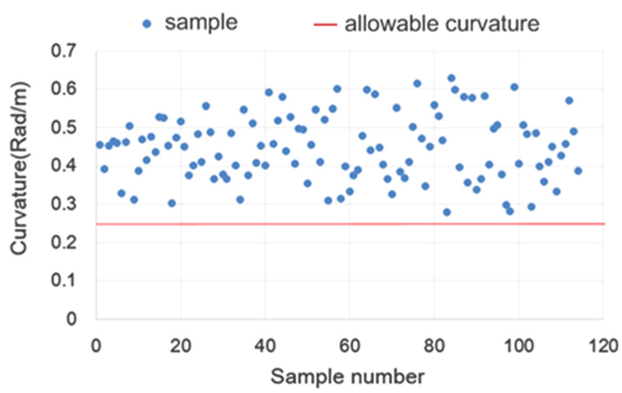

Fig. 5 Samples' curvature responses

The samples whose responses fail to meet the remaining constraints are removed to filter out the bad samples before constructing the surrogate model; 114 samples satisfying all of the specified constraints are retained. However, all of them fail to meet the curvature criterion ($C \leq 0.25$ rad/m), as shown in Fig. 5. This result indicates the difficulty of designing a riser configuration in extremely shallow water, because a satisfactory design cannot be found by a random and uniform sampling strategy (optimal LHS).

4.5 Construction and Validation. The Kriging and RBF models are constructed based on the samples and corresponding responses obtained above. They are constructed using Isight 5.0, an integration platform for a simulation-based design process [41].

The Gaussian correlation function is chosen to construct the Kriging model. It is expressed as

$$\mathrm{corr}(\mathbf{x}^{(i)}, \mathbf{x}^{(j)}) = \prod e^{\theta_k} |\mathbf{x}^{(i)} - \mathbf{x}^{(j)}|^2 \tag{9}$$

where θ_k is the correlation parameter, which is obtained by maximizing the likelihood estimation.

Isight uses a variable power spline RBF that can be tuned to approximate a large number of other functions and is given by

Table 2 R^2 value comparison of the Kriging and RBF models

Response	R^2 of Kriging model	R^2 of RBF model
Max. curvature, C	0.75	0.95
Max. effective tension, T	0.75	0.97
Max. hang-off angle, θ	0.87	0.98
Min. seabed clearance, d	0.92	0.99
Total length redundancy, ΔL	0.89	0.99

$$h(x) = \|x - x_i\|^c \tag{10}$$

where $\|x - x_i\|$ is the Euclidian distance. c is a shape function variable between 0.2 and 3, which is optimized for a minimum of the errors for $N-1$ data points.

Next, a comparison of the models' accuracy is performed to find a better model for this design task. To assess the quality of the surrogate model, the cross validation (CV) scheme [42] is used in this work to perform the error analysis, in which the sample data are divided into subsets; and one set is removed from training to act as the testing set at a given time. In addition, 10 points from the total samples are used for the testing. The R^2 value in the CV scheme is used to validate and compare the two constructed models. The value of R^2 closer to 1 indicates that a higher accuracy of approximation is achieved. The R^2 values from the two models are listed in Table 2.

According to Table 2, the RBF approach provides a better approximation for this problem. The Kriging approach presumes the global functional form and identifies the maximum likelihood estimators, so it is typically difficult to obtain and use [21]. In addition, the RBFs are known as local approximation networks as they are composed of a number of elements that primarily consider the approximation regarding a specific area of the input space [43]; as a result, they can provide arbitrarily good approximations to a prescribed function of a finite number of real variables [37]. As the dynamic behaviors of a steep wave riser in extremely shallow water are very sensitive to the design parameters and the implicit function might be highly nonlinear and multimodal, local model approaches such as RBF are easier to construct.

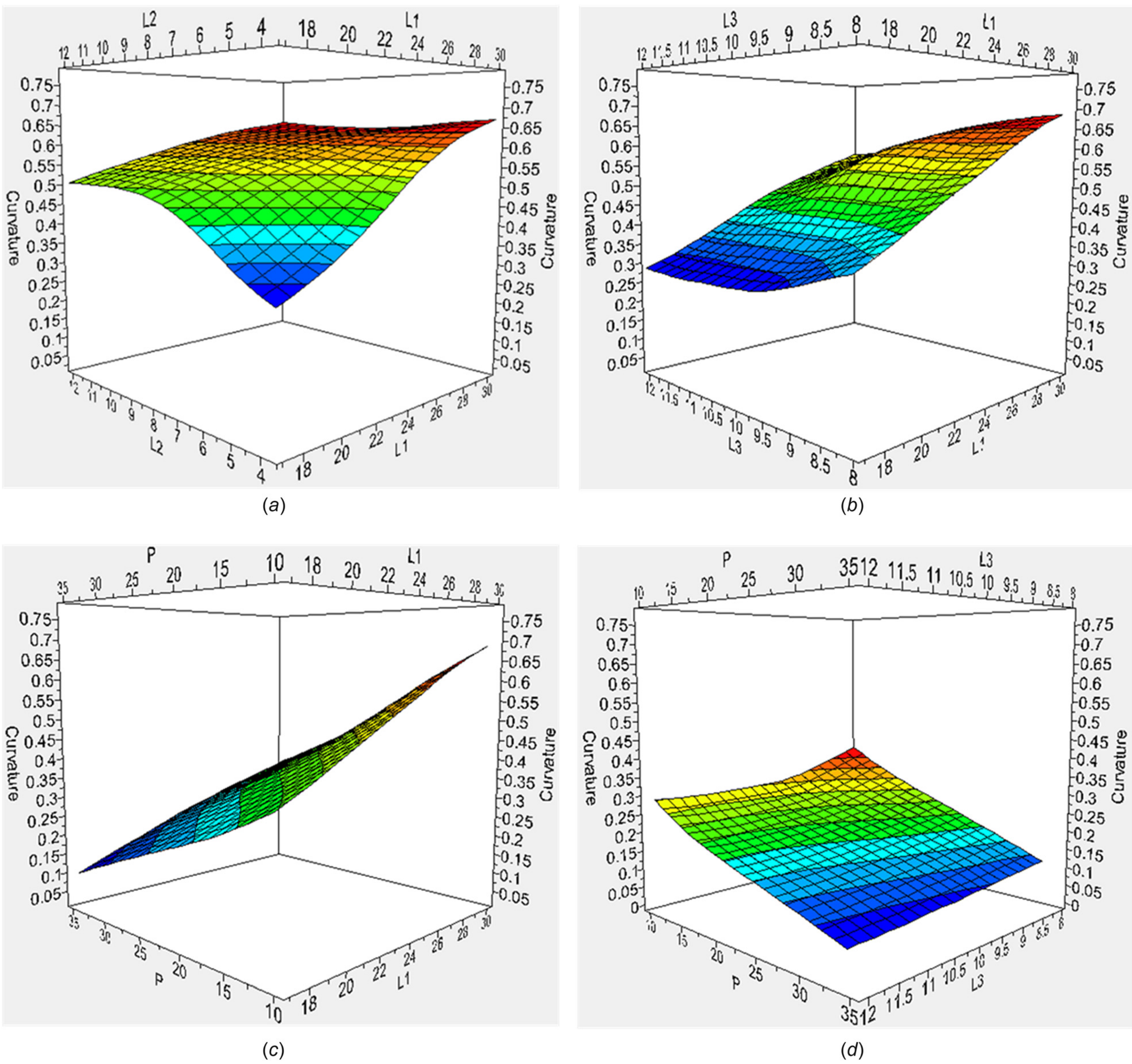

Fig. 6 Variables versus curvatures of the RBF model: (a) L_1, L_2 versus curvature, (b) L_1, L_3 versus curvature, (c) L_1, P versus curvature, and (d) L_3, P versus curvature

Based on the above analysis, the RBF model is selected as the surrogate model to perform the subsequent optimization for the riser configuration. Some three-dimensional graphs of the RBF model between the variables and curvature responses are shown in Figs. 6(*a*)–6(*d*). It is clear that the curvature is not a monotone function of the variables and may have several extreme values in the design space. This observation indicates that the optimization design is difficult to perform using the traditional gradient-based design method. Moreover, a global algorithm is required to perform the optimization while avoiding a local optimum.

5 Optimization

5.1 Optimization Strategy. A hybrid optimization strategy, which is composed of two classical algorithms that are applied sequentially in two steps, is used in this study. First, the MIGA [32] is used to find an approximate solution, which is the global optimum of the model. Next, NLPQL [33] is performed using the solution obtained by MIGA. MIGA is a well-known global optimization algorithm that has better efficiency than the traditional GA, but the calculation time would be increased remarkably if a higher accuracy was required. Thus, the combination of the MIGA and an efficient gradient algorithm such as NLPQL will simultaneously improve the possibility of finding the global optimum and the efficiency. The optimization is also achieved using Isight 5.0 [41].

We can see from Table 3 that a global optimal design is successfully found by MIGA, starting from the 0 point of each design variable, but it is an approximate solution and the curvature does not satisfy the criterion (MBR $<$ 0.25 rad/m). After the NLPQL optimization, an accurate and satisfactory design is obtained. The running time of the entire optimization process is approximately 13 mins and 24 s using an Intel i5 3.20 GHz CPU with 8 GB RAM; most of the time was taken by the MIGA. The NLPQL optimization takes less than 1 s, which greatly improves the efficiency of the optimization.

5.2 Results and Discussion. We can validate the final optimized design (from NLPQL) in Orcaflex and treat the results as the reference value. The comparison is performed and shown in Table 4.

According to Table 4, the responses obtained from the RBF-model-based optimization results show good accuracy. The objective function of the curvature is optimized to 0.239 rad/m, which represents a 15% improvement compared with the minimum values of 0.282 rad/m from the samples. More importantly, the design criterion of the curvature is satisfied. Note that despite the failure of all of the samples to meet the curvature criterion ($C \leq 0.25$ rad/m), a feasible and optimal design of the riser configuration for such an extremely shallow water application can be found with the established optimal model. In addition, the accuracy and efficiency for this optimization problem are relatively satisfactory.

Table 3 Optimization results

	Starting point	MIGA (step 1)	NLPQL (step 2)
L_1	0.0	29.4	29.9
L_2	0.0	11.8	11.2
L_3	0.0	9.9	12.0
P	0.0	36.0	38.7
C	—	0.259	0.238
Running time	—	13′23″	1″

Table 4 Comparison between the optimization and simulation results

	C	T	θ	d
Optimization design	0.238	14.5	75.0	9.6
Reference value	0.239	15.2	76.0	9.5
Error (%)	0.42	4.61	1.3	0.42

The above work is based on the regular wave approach, which may be subject to severe bias in dynamically sensitive systems [1]. In practical design, the critical cases should be verified by the irregular wave approach. Therefore, a 3-hr time domain analysis is performed to verify the optimal design obtained above. The Jonswap spectrum is used (Hs = 4.7 m and Tp = 8.6 s), and the extreme curvature value is calculated from the Rayleigh distribution [40]. The 3-hrs most probable maximum value for curvature from the calculation is 0.238 rad/m, and the maximum value with risk factor 1% is 0.248 rad/m. Obviously, the optimal design is validated to meet the design criteria.

6 Conclusions

The riser configuration design in extremely shallow water is rather challenging because of the narrow feasible domain in the design space and the expense of the simulations. In this paper, a surrogate-model-based optimization of a steep wave riser is studied to perform an urgent design for an oil-spill incident in extremely shallow water. An optimized design is finally obtained with relatively high accuracy and efficiency using the optimization based on the RBF model. Although all of the samples associated with the construction of the surrogate models fail to meet the curvature criteria, an optimized design was found to fulfill all of the specified criteria with high accuracy. This result suggests that the technique of surrogate-model-based optimization is effective for solving the problem described in this paper. More generally, this approach may have great potential to meet the challenges in some other extreme conditions because it can find a feasible solution with high probability.

It is difficult to perform a detailed comparison of the efficiency between surrogate-model-based optimization and the traditional method because the traditional design of riser configuration is very experience-dependent; in particular, it may take a designer from several days to several months to solve the problem considered in this paper. Nevertheless, the surrogate-model-based optimization technique shows good efficiency; the simulation required several hours in total in this case, with most of the time spent on the samples' simulation. In other words, the number of samples, which greatly affects the efficiency of this technique, is influenced by many factors including the surrogate modeling approaches, the correlation of the design variables, and the complexity of the implicit functions. In this work, we paid more attention to the feasibility of this approach rather than its efficiency. As a result, the number of samples would be reduced significantly if more studies are performed on the factors mentioned above.

An effective approach for modeling the riser configuration optimization problem is to simplify the riser configuration design into a single-objective optimization problem and then take as few of the load cases as possible. In this way, other design criteria and load cases can be accounted for by means of designing some constraints and providing margins. However, this approach is heavily dependent on the designer's experiences and physical conceptions, which requires additional research effort. Nevertheless, the response of the flexible riser system might change significantly for different load cases, and it is the most challenging problem for the application of optimization techniques. Therefore, more complex problems could be encountered in a practical riser design for which multi-objective optimization based on a surrogate model might be introduced in the near future.

Finally, it is very efficient to use the regular wave approach for the construction of surrogate models. However, the riser system should be investigated to identify the most unfavorable loading conditions, considering the eigenvalues of the riser system, the floater motions, and so on. Furthermore, the results should be always verified with the irregular wave approach. In addition, the use of the irregular wave approach in surrogate-model-based optimization is worthy of further study.

Acknowledgment

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