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A hybrid fuzzy inference model based on RBFNN and artificial bee colony for predicting the uplift capacity of suction caissons

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ABSTRACT

The suction caisson is an essential part of the foundation system used in offshore platforms. The failure of a single suction caisson may cause the collapse of an entire offshore system. Hence, accurately predicting the uplift capacity of suction caissons is of critical importance to platform function and reliability. This study proposes the intelligent fuzzy radial basis function neural network inference model (IFRIM) to predict the uplift capacity of suction caissons. IFRIM is a hybrid of the radial basis function neural network (RBFNN), fuzzy logic (FL), and artificial bee colony (ABC) algorithm. In the IFRIM, FL deals with imprecise and uncertain information; RBFNN acts as a supervised learning technique to address fuzzy input–output mapping relationships; and ABC searches for the most appropriate parameter settings for RBFNN and FL. Comparison results show IFRIM to be the fittest model for predicting the uplift capacity of suction caissons in terms of accuracy and reliability. A 10-fold cross-validation approach found that the IFRIM reduced the *RMSE* and *MAPE* at least 70% and 90%, respectively, below other tested models.

1. Introduction

Suction caisson systems (also referred to as suction anchors, suction piles, and suction buckets) were first introduced by Senpere and Auvergne [39] in the early 1970s as mooring anchors. Today, the offshore drilling industry uses these systems as a critical part of foundation systems for anchoring offshore platforms to the seafloor [9,14]. Chakrabarti [8] calculated that over 10,000 offshore platforms had been installed prior to 2005. In 2004, more than 485 suction caissons were installed at over 50 locations [4]. The number of suction caisson installations has increased rapidly in line with the steady increase in oil and gas platforms built to exploit oil and gas finds in ultra-deep water.

The preference for using suction caissons for offshore platforms' foundations reflects the multiple advantages of this method over alternatives. These advantages include: (1) simple design: suction caissons consist of a steel tube closed at the top and open at the bottom (see Fig. 1a); and (2) simple installation: water is pumped out of the caisson at the top to reduce pressure inside the caisson relative to the surrounding water (see Fig. 1b). This method makes suction caissons significantly more simple to install than traditional pile foundation methods [1]; (3) fast installation: the relatively short installation time compared to traditional methods reduces weather-related risks and minimizes equipment requirements and significantly reduces the costs of construction [19]; and (4) suction caissons have superior resistance to lateral loads and uplift capacity than alternatives [19].

However, the overall system reliability of suction caissons has been found to be less sturdy than fixed platforms [17]. The failure of a single suction caisson may result in the collapse of an offshore platform structure that may severely impact the project owner's finances, pollute the environment, and cause loss of life. Randolph and Gourvenec [36] stated that the financial costs of offshore structure failure may be considerable. Hence, a reliable design for suction caissons is a critical issue in order to avoid undesired and extremely costly failure. The accurate assessment of uplift capacity is the key to suction caisson reliability.

In fact, adequately estimating the uplift capacity of a suction caisson is a challenging task due to the complex behavior of suction caissons during the loading process. A passive suction is created during uplift loading that increases the foundation pullout capacity. Passive suction contributes to the overall pullout capacity through the development of end-bearing resistance at the base of the caisson and concurrent increases in the effective stresses inside the caisson that lead to higher skin friction along the inside wall of the caisson. At the same time, the uplift capacity of suction caissons is governed by many factors such as the composition of surrounding soil, the position and angle of the pullout load, and interaction between the soil and the caisson.

A number of laboratory and field tests have been conducted to handle the aforementioned problems [24,37,43]. However, these methods are quite costly and time-consuming and subject to various limitations. Finite element method (FEM)-based models have also been used to predict the uplift capacity of suction caissons [15,42,48]. Despite their

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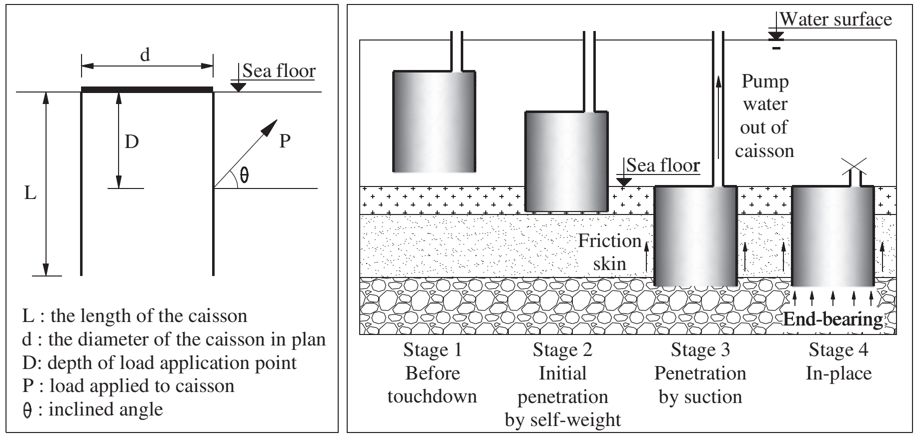

(a) Suction caisson definition sketch (b) Installation process of suction caisson

Fig. 1. Sketch and installation process of suction caisson.

ability to address the disadvantages identified in laboratory and field tests, FEM-based models are limited to specific case characteristics and thus require the design of different, simplified equations relevant to each case [34]. Therefore, developing a reliable method able to adequately predict the uplift capacity in a broad range of conditions is imperative and of paramount importance.

Artificial intelligence (AI)-based inference models such as the artificial neural network (ANN) and fuzzy logic (FL) are viewed increasingly as viable alternative approaches to addressing the uplift capacity prediction problem of suction caissons. AI-based inference models simulate human inference processes. They infer new facts from previously acquired information and change adaptively in response to changes in the historical data. Hence, AI-based inference models represent a powerful data-modeling tool that captures and represents complex input–output relationships. AI techniques thus currently enjoy widespread use. These techniques are generally perceived as effective in solving both prediction and optimization problems in civil engineering related to structures and infrastructures [20,21], geotechnical and transport engineering [2,45], construction management [11,12], and materials engineering [18].

Proposed by Broomhead and Lowe [7], RBFNN has been used widely in various fields because this model possesses features that are more advanced than the conventional back-propagation neural network (BPNN). Firstly, RBFNN may be trained in a short time due to its simple topology structure [27]. Secondly, RBFNN typically completes a good training process using a two-stage training scheme [46]. Thirdly, RBFNN is easy to implement due to its small number of control parameters [41]. Finally, RBFNN has been found to deliver superior performance in handling many disparate problems [23,33,40].

FL is able to absorb presumptions, maintain subjectivity, and handle vague information [10]. Rahman et al. [35] stated that input information related to the uplift capacity of suction caissons such as soil strength characteristics often comprises variants and uncertainties. Hence, FL is a competitive choice for solving uncertainty in the uplift capacity of suction caissons. However, FL and RBFNN have not been previously used together to address the problem of uplift capacity. In the AI field, FL may be fused with different techniques to enhance the approximate reasoning capability of inference models [13]. Therefore, the fusion of RBFNN and FL is regarded as an efficient inference model to predict the uplift capacity of suction caissons.

Users must specify appropriate values for control parameters simultaneously to achieve the greatest success using RBFNN and FL. Pre-specification of RBFNN parameters including the hidden neuron number (N_n) and the Gaussian function width (σ) significantly affects performance of the constructed RBFNN model [44,49]. While optimal parameter values significantly increase model performance, suboptimal parameter values undermine the predictive capacity of the model. Meanwhile, the ability of FL to handle vagueness and uncertainty depends substantially on appropriately configuring the MF, selecting an appropriate number of rules, and selecting proper fuzzy set operations. This process is subjective in nature and reflects the context in which a problem is viewed, with increasing problem complexity increasing the inherent difficulties in both the configuration of the MF and the construction of appropriate rules [13].

In practice, identifying the most appropriate set of parameters for a model is an optimization problem. Hence, combining RBFNN and FL with the artificial bee colony (ABC) [28] search engine offers a potentially efficient solution. Proposed by Karaboga in 2005, ABC is a swarm intelligence-based optimization algorithm inspired by honeybee foraging behavior. Its relatively small number of control parameters makes ABC flexible and easy to execute for novice users [31]. Researchers have demonstrated that ABC is superior to other algorithms in identifying optimal solutions [29,30]. Furthermore, ABC has been demonstrated to be a reliable tool in combination with other data mining techniques [25]. ABC is thus a potentially useful search engine in combination with RBFNN and FL.

This study proposes a novel fuzzy inference model, the intelligent fuzzy radial basis function neural network inference model (IFRIM), for predicting the uplift capacity of suction caissons. The IFRIM is a hybrid of RBFNN, FL, and ABC. Benefits of this model include its ability to operate independent of human intervention, tackle the uncertainty inherent in the uplift capacity problem, and provide greater prediction accuracy than current models.

The remainder of this paper is organized as follows: the second section reviews related research works; the third introduces the IFRIM model; the fourth describes the data collection process; the fifth validates and analyzes IFRIM performance and compares simulation results; and the last presents conclusions.

2. Literature review

2.1. Previous works

In recent years, numerous studies have proposed AI techniques to address the uplift capacity problem of suction caisson. Rahman et al. [35] first used a three-layered back-propagation neural network (BPNN) to predict the uplift capacity of suction foundations using 62 individual test results. Pai [34] proposed a hybrid neuro-genetic network (NGN) prediction model for the uplift capacity that used a genetic algorithm to determine the weights of BPNN.

Recently, Alavi et al. [1] and Gandomi et al. [19] applied a variant of genetic programming (GP) to predict and formulate the uplift capacity