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A Data-driven Macroelement Model for Suction Buckets in Sand

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ABSTRACT: Macroelement models characterise the macroscopic behaviour of foundations in terms of resultant forces and displacements at a reference point within the foundation. Conventional macroelement models are governed by constitutive equations whose parameters are calibrated against experimental or numerical results; however, the models' response is not necessarily accurate for varying conditions when adopting a unique set of parameters. Data-driven approaches can be more flexible as they are not bounded by any mathematical formulation and so can fit the underlying foundation behaviour with greater accuracy. A new data-driven macroelement (DdM) model for suction buckets is developed in this paper. Firstly, a database of 3D finite element (FE) analyses was created to train the DdM model. The 3D FE analyses considered suction bucket foundations installed in sand. A state-parameter dependent constitutive model incorporating a nonlinear elastic overlay model was adopted with parameters calibrated for the Dunkirk PISA site. The database includes variations in the foundations embedment-to-diameter ratio, initial relative density of the sand and the applied loading direction. An artificial neural network (ANN) was then employed as the underlying DdM model. The ANN was trained to predict the foundations force components (vertical, horizontal and bending) given the current deformation state of the foundation. The performance of the ANN was extensively validated, demonstrating an excellent generalisation ability to unseen data. Overall, the proposed DdM model demonstrates the feasibility and potential of this class of models for future design of suction buckets.

Keywords: suction buckets, macroelement, machine learning, surrogate models, neural networks

1 INTRODUCTION

Due to their efficiency, macroelement models (Byrne, 2009) can be useful to simulate the behaviour of suction buckets in soil-structure interaction analyses. Macroelement models describe the foundation response in terms of displacements and resultant forces at a single point within the foundation. These models are commonly governed by mathematical formulations, and their parameters are typically calibrated against experimental or numerical results. One important drawback of conventional macroelement models is the frequent need to be recalibrated for different loading or soil conditions.

The latter limitation may be addressed by data-driven surrogate models that have been recently introduced as an alternative to conventional macroelement models for suction buckets. Zhang et al. (2020) developed a model using a long short-term memory neural network that could replicate the results from a validated numerical model. However, the study was restricted to two-dimensional loading conditions, i.e. zero vertical force, and so has limited practical interest for design purposes. Yin et al. (2023) trained a feedforward neural network to predict the response of suction buckets considering three-dimensional loading. While the neural network showed very good predictive capabilities, it was effectively limited to the prediction of foundation capacity as the numerical model used to generate the training data did not consider the nonlinear variation of soil stiffness.

This paper aims to extend the scope of previous studies by developing a data-driven macroelement (DdM) model suitable for the design of foundations supported by suction buckets. To this end, the proposed DdM model was fitted with data generated by a 3D numerical model adopting a state-parameter dependent sand constitutive model coupled with a nonlinear elastic model. The resulting model can predict the foundation's reaction curves for the

vertical, lateral and rotational components under any arbitrary loading conditions. The excellent performance of the DdM model highlights the potential of this type of data-driven approach as a viable alternative for the design of suction buckets.

2 NUMERICAL MODEL

The data-driven macroelement model was trained with data generated from analyses conducted with the finite element software PLAXIS 3D (Bentley Systems, 2024). The analyses consisted of a single suction bucket installed in a uniform sand layer and subjected to multiaxial loading comprising vertical, horizontal and rotational components under drained conditions. The latter implies that long-duration loading is simulated. The specifics of the model setup are described in the following sections.

2.1 Geometry

The model geometry is depicted in Figure 1. It can be observed that, due to symmetry considerations, only half of the domain was simulated and discretised using 10-noded tetrahedral elements with second-order interpolation for displacements (Bentley Systems, 2024). The adopted diameter of the bucket D was 8 m in all the analyses while the bucket's length L was varied, as explained in Section 3.1. The thickness of the skirt t_{skirt} was adopted as 0.064 m such that D/t_{skirt}=125; the lid was assumed to be rigid, rendering its thickness irrelevant. As shown in Figure 1, the dimensions of the modelled domain were set relative to the bucket's dimensions: the depth of the model was adopted as 4L, the width of the side parallel to the symmetry plane as 15D and that of the side perpendicular to it as 7.5D. Given that the model was defined parametrically, both in terms of the extent of the domain and the characteristics of the suction bucket, extensive mesh sensitivity studies were carried out to ensure that, for various possible geometries, sufficient accuracy would be achieved (i.e. further refinement was seen not to affect the results).

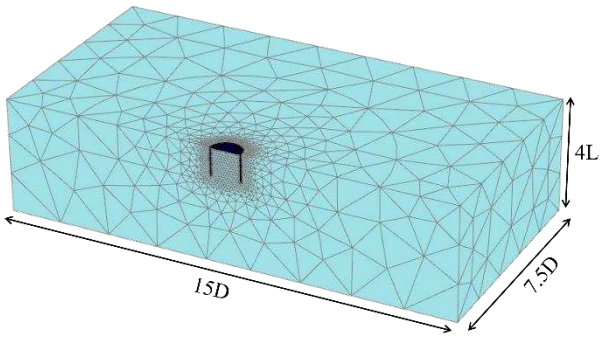


Figure 1 Mesh and dimensions of the numerical model

6-noded shell elements were employed to simulate the suction bucket. The contact interaction between the foundation and the surrounding soil was modelled by including 12-noded interface elements between the lid and the soil, as well as around the skirt.

2.2 Material modelling

The mechanical behaviour of the sand was simulated with the constitutive model proposed by Taborda et al. (2022) and implemented in PLAXIS 3D via the UDSM facility (Taborda et al., 2024). The constitutive model incorporates critical state soil mechanics and the state-parameter concept, as defined by Been and Jefferies (1985), in conjunction with the Mohr-Coulomb failure criterion, where the shearing resistance φ_c and dilatancy ν_c angles are dependent on the state parameter ψ. At denser-than-critical states ($\psi < 0$), the available strength is larger than that at critical-state. As soil approaches critical state (i.e. ψ increases towards 0.0), the shearing resistance angle φ_c converges towards the critical-state angle φ_{CS} and the dilatancy angle ν_c towards zero. For looser-than-critical states ($\psi > 0$), the shearing resistance angle φ_c is set to be equal to the critical-state angle φ_{CS} and the dilatancy angle ν_c is set to zero. Prior to yielding, the response of the material is controlled by the model described in Taborda et al. (2016) in which the soil's shear and bulk stiffness values vary with stress according to a power law and with strain using a modified hyperbolic relationship.

In this study, an existing model calibration for the Dunkirk site was employed (Pirrone and Taborda, 2023). The calibration was initially solely based on laboratory and field data (Taborda et al., 2020) and subsequently included the back analysis of key model parameters against one of the pushover tests on monopiles from the PISA project. The whole set of model parameters is listed in Table 1.

The interface elements introduced between the foundation and the soil adopted Coulomb frictional behaviour. The adopted interface angle of shearing resistance φ_{inter} was 22.6° which corresponds to a strength equivalent to 2/3 of the critical-state strength. A zero dilatancy angle was prescribed for the Coulomb interface. The stiffness of the interface was simulated according to the following stress-dependent power law for the oedometer stiffness modulus:

$$E_{oed,i} = E_{oed}^{ref} \left(\frac{\sigma_n'}{\sigma_{n,ref}'} \right)^z \quad (1)$$

where $\sigma_n^{'}$ is the effective normal stress at the interface, $\sigma_{n,ref}^{'}$ is the reference normal stress, E_{oed}^{ref} is the reference oedometer modulus and z is the parameter governing the stress dependency. The values for E_{oed}^{ref} and z were determined such that the equivalent shear modulus of the interface G_i matched the profile of the shear modulus at small strains (corresponding to the initial stress conditions) within the sand. This was achieved by considering that the shear modulus G_i is defined as:

$$G_i = \frac{(1-2\mu_i)}{2(1-\mu_i)} E_{oed,i} \quad (2)$$

where μ_i=0.45 (Bentley Systems, 2024). Correspondingly, $\sigma_{n,ref}^{'}$ was taken as 101.3 kPa, z was adopted as 0.5 (the same as the analogous parameter m in the sand model, see Table 1) while E_{oed}^{ref} adopted different values depending on the initial void ratio of every given analysis.

The steel forming the suction bucket was simulated as a linear elastic material adopting a Young's modulus of 200 GPa and a Poisson's ratio equal to 0.3.

Table 1. Model parameters for Dunkirk sand.

Parameter	Value
Elasticity	
G_{ref} (kPa)	87500.0
μ	0.17
p'_{ref} (kPa)	101.3
m	0.50
a	$2 \cdot 10^{-4}$
b	1.4
$R_{G,min}$	0.357
Critical state	
$e_{CS,ref}$	0.91
λ	0.135
ξ	0.179
Plasticity	
φ_{CS}	32.0
k_1	1.567
l_1	1.527

2.3 Initial and boundary conditions

The value of the coefficient of earth pressures at rest K_0 at the start of the analyses was established according to $K_0 = 1 - \sin\varphi_{CS}$. A hydrostatic pore water pressure was adopted, with the phreatic level set at the top of the model.

As shown schematically in Figure 2, the foundation was loaded by prescribing horizontal h and vertical v displacements, and a rotation θ to the rigid lid. The loading paths and magnitudes considered are outlined in Section 3.1.

Lastly, the displacements of the bottom boundary of the model were restricted in all directions; those along the vertical boundaries were restricted in the direction normal to such boundaries.

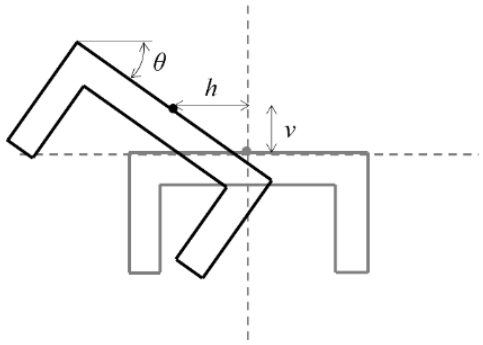


Figure 2 Displacements and rotation applied to the suction bucket

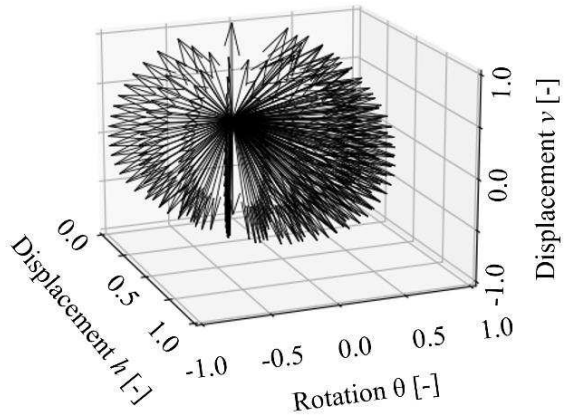


Figure 3 Loading directions in v-h-θ space considered in the numerical database

3 NUMERICAL DATABASE

3.1 Sampling plan

The numerical database comprised analyses where the ratio *L/D* was varied between 0.5 and 1.5, while the initial relative density D_r of the sand assumed values between 50% and 100%. Moreover, to generate data that could be informative about the bucket's response to arbitrary loading, the analyses in the database also adopted varying loading paths in the *v-h-θ* space. A total of 230 loading directions were considered, unit vectors for each of these directions are shown in Figure 3. The bucket was both vertically pushed into and pulled out of the ground so that, unlike previous studies (Yin et al., 2023), the DdM model could subsequently be trained to predict the behaviour of the bucket under tensile vertical loads.

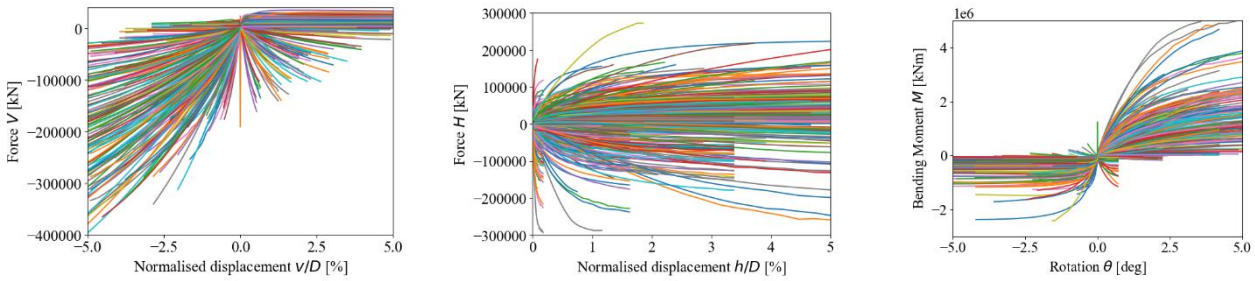
This could for example be relevant to the modelling of suction bucket jackets subject to sustained tension loads associated with operational wind loading. Threshold values were specified in each loading direction such that the analysis would terminate once the applied displacement/rotation in one of the directions v-h-θ reached its corresponding threshold. The adopted threshold values were v/D=±5%, h/D=5% and θ=±5°. These values were thought to be sufficiently large for the bucket to be pushed beyond typical serviceability conditions.

The *MaxPro* (Maximum Projection Designs) package (Shan and Joseph, 2018) was employed to generate the sample design for the database. The sample design effectively specified the ratio L/D, D_r and the loading path (given as an index ranging between 1 and 230) to be employed in each of the analyses. *MaxPro* maximises the distance between sample points in all the projection subspaces of the sampling space which is meant to provide an optimal approach for generating data for the creation of surrogate models. Moreover, *MaxPro* allows for the generation of sample batches of arbitrary sizes which is a useful feature in surrogate generation, as the number of samples required for an accurate surrogate to be obtained is not usually known beforehand. The DdM model was trained with an increasing number of analyses, in increments of 50 new analyses. The final DdM model was trained with 600 analyses which proved sufficient for it to achieve an excellent performance.

3.2 Results

Figure 4 depicts the force-displacement curves for the 600 analyses of the database where forces V and H are those acting in the vertical and horizontal directions, respectively, and M is the bending moment. Note that the forces and bending moments were obtained from the analyses as the reactions associated with the prescribed displacements and rotation.

Many of the curves show forces with the opposite sign of the corresponding applied deformations. This feature of the response highlights the coupling between the various loading components: a negative reaction force in a given direction develops when the other load components push the associated displacement to be larger than the value actually prescribed for that loading increment. It is worth noting that, since the DdM model was trained directly with data from the analyses, it intrinsically accounts for the coupling between the various loading components.



(a) Force V-displacement v (b) Force H-displacement h (c) Bending moment M-rotation θ

Figure 4 Foundation reaction curves from all analyses of the database

4 DATA-DRIVEN MACROELEMENT

4.1 Training of DdM model

A feedforward neural network, subsequently referred to as ANN, from the package *Keras* (Chollet, 2018) was used to construct the DdM model. The ANN was trained to predict forces V, H and M given the ratio D/L of the bucket, sand relative density D_r, displacements v and h, and rotation θ.

The numerical database was divided into training (70%), validation (20%) and testing (10%) datasets. The data was split randomly in such a way that all data points from a given analysis were sent to the same dataset. This allowed for a rigorous inspection of the generalisation ability of the model as the input variables on the testing dataset were not used at all during training. To facilitate training of the ANN with inputs on different scales, the input features were normalised individually by their maximum absolute value as encountered in the training dataset such that each feature ranged between -1.0 and 1.0.

The ANN configuration used to build the DdM model is described in Table 2. The number of layers, number of neurons per layer and the learning rate of the ANN were calibrated using a hyperparameter tuner based on Bayesian optimisation that is available in Keras. The final ANN configuration was stored at

the iteration (epoch) where the mean absolute error on the validation dataset was lowest.

Table 2. Hyperparameters adopted in the Keras ANN.

Hyperparameter	Value
Optimiser	Adam
Number of layers	3
Number of neurons per layer	2432
Activation function	Rectified Linear Unit (ReLU)
Learning rate	0.00080
Batch size	32

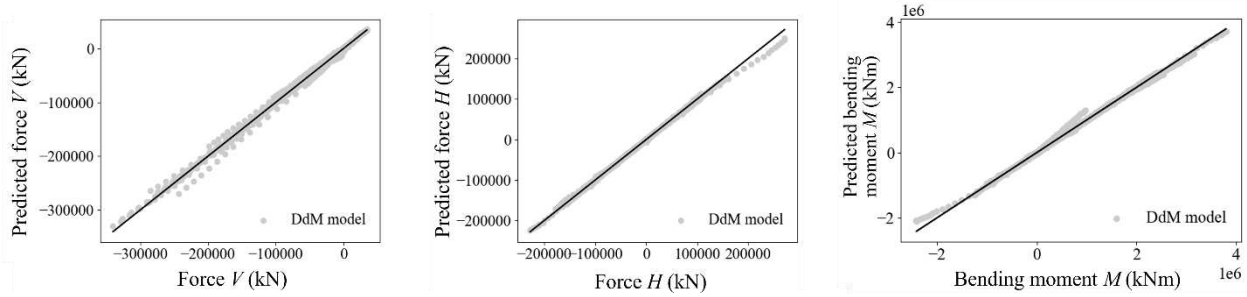
4.2 Model evaluation

Figure 5 presents regression plots of predicted forces V, H and M for the testing dataset. It can be observed that the DdM predictions generally lie in a narrow band around the 1:1 black line which means the model is performing well. The coefficient of determination R^2 for the three forces was obtained as 0.998. This is a high score as R^2 equal to1.0 would signify a perfect match between predictions and target values. The mean absolute errors across the testing dataset were found to be 510.7 kN, 442.3 kN and 4822.6 kNm for the force V, force H and bending moment M, respectively. Since the magnitude of the three forces are considerably different (and so are their units), in order to compare the performance of the DdM for the different force components it is useful to also consider a relative error metric such as the weighted absolute percentage error (WAPE) which is defined as:

$$WAPE = \frac{100}{\sum_{i=1}^{N}|T_i|}\sum_{i=1}^{N}|T_i - P_i| \qquad (3)$$

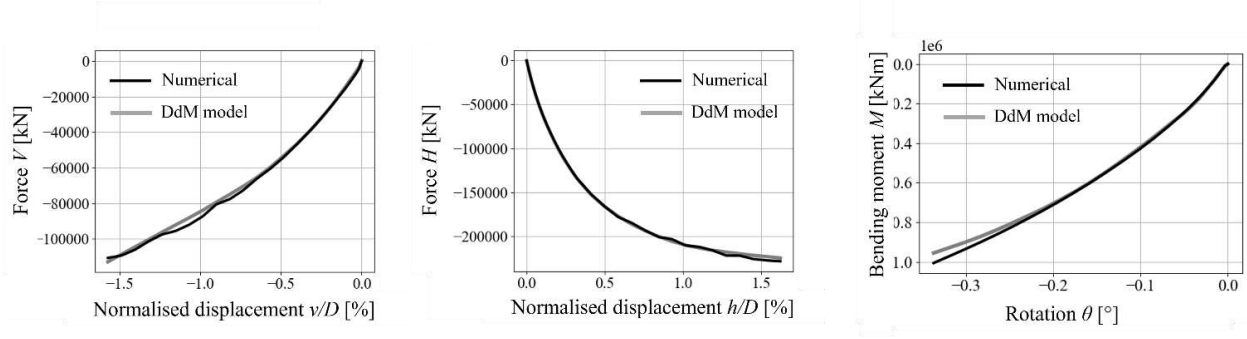
where T are the target data, P the predictions and n the number of data points. Values of the WAPE equal to 3.0%, 2.6% and 2.5% were obtained for V, H and M, respectively. These values suggest that the predictive capabilities of the DdM model are similar for the three loading components.

In addition to the global performance metrics, the DdM model was carefully evaluated in terms of the actual prediction of reaction curves for each of the analyses from the testing dataset. Figure 6 shows the reaction curves predicted by the DdM model, and their numerical counterparts, that yielded mean absolute errors in the 25th percentile (i.e. 75% of the analyses were more accurate) for each of the loading components out of all the analyses in the testing dataset. An excellent agreement with the numerical data can be observed. Since these results are not among the top percentiles in terms of performance, they provide evidence of the overall excellent ability of the DdM model to replicate the response of the numerical model.



(a) Force V (b) Force H (c) Bending moment M

Figure 5 – Regression plots of predicted forces against the testing dataset.



(a) Force V (b) Force H (c) Bending moment M

Figure 6 – DdM predictions against numerical results for the 25th percentile error of the testing dataset.

5 POTENTIAL APPLICATIONS TO FOUNDATION DESIGN

Data-driven macroelements are foreseen to enable rapid and efficient optimisation of suction buckets during concept design. For complex sites with challenging geology, having a macroelement model will enable the designer to assess viable foundation sizes that takes into account position-specific geotechnical data. This is particularly valuable at early design stages where a wide envelope of loading conditions (for example from different models of wind turbine generators, or variations in substructure type) may exist. For soil-structure interaction analyses (e.g. earthquake loading), macroelement models are also seen as a superior alternative to nonlinear springs derived using a limited number of pushover models that may not accurately capture the cross-coupling responses.

It is foreseen that macroelement models can be further extended to capture other soil types (e.g. fine grained soils), multi-layered soils and undrained loading conditions.

6 CONCLUSIONS

This paper presents an exploratory study focussing on the development of data-driven macroelement models for suction buckets in sand. The proposed DdM model was able to closely replicate the results yielded by a complex numerical model adopting a state-parameter dependent constitutive model for sand, along with nonlinear elasticity. A substantial range of geometries ($0.5 \leq L/D \leq 1.5$) and relative densities ($50\% \leq D_r \leq 100\%$) have been explored, ensuring a wide applicability of the developed DdM model. Outside these ranges, the use of the model has not been investigated and therefore must be approached with caution, with additional numerical analyses required.

In conclusion, this research demonstrates that this type of macroelement models can provide significant enhancements in efficiency given their reduced computational cost, while maintaining the complexity and accuracy of advanced 3D models.

AUTHOR CONTRIBUTION STATEMENT

First Author: Conceptualisation, Methodology, Data curation, Writing- Original draft. **Second Author**: Conceptualisation, Software, Funding, Supervision, Writing- Reviewing and Editing. **Third Author**: Conceptualisation, Funding, Supervision, Writing- Reviewing and Editing. **Additional Authors**: Conceptualisation, Writing- Reviewing and Editing.

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