Intelligent **Drive**ability Forecasting for Offshore Wind Turbine Monopile Foundations (iDRIVE)

Supergen Summary Report

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INTRODUCTION

Offshore wind turbines (OWT) are typically supported by driven open-ended steel piles as either one of multiple axially loaded foundations for a jacket structure or single, large-diameter laterally loaded monopiles. Typical jacket piles range in diameter from 2.5-3m with length-to-diameter ratios (*L*/*D*) between 7 and 20 (Barbosa, 2021). The size of monopile foundations is increasing rapidly; in current and future projects diameters range from 6-11m with *L*/*D* ratios of 3-5 (Siegl et al., 2020). Both foundation types are installed in the offshore environment using large hydraulic impact hammers. When a hammer strikes a pile, a stress wave is generated which travels down the pile to the tip. Prior to the installation works pile driveability analyses are used to (i) choose the optimal hammer size to safely install the pile and (ii) ensure that driving does not induce excessive fatigue stresses in the pile.

Driveability analyses use one-dimensional stress wave theory to model the forces and displacements in the pile during driving. The analysis requires information about the pile geometry, the pile penetration, the hammer characteristics and an empirical method to predict the soil resistance to driving (SRD) or short-term axial capacity provided by the soil. The SRD for a fully coring open-ended pile is given by:

$$SRD = \pi\left(D\int_0^L \tau_f \, dz\right) + A_{ann}q_{ba} \tag{1}$$

where τ_f is the total internal and external driving shaft resistance, L is the pile embedment, A_{ann} is the annular steel area and q_{ba} is the end-bearing resistance acting on the steel annulus. An effective SRD formulation is capable of capturing the primary physical mechanisms of axial pile behaviour during installation, i.e.: (i) links between penetration resistance and in situ tests such as the cone penetration test (CPT) and (ii) reductions in local effective stresses at any given soil horizon with increasing pile penetration, a phenomenon commonly referred to as 'friction fatigue' (Heerema, 1978). Current empirical SRD approaches were developed through back analysis of pile driving records in sands, clays and rocks (e.g. Toolan and Fox, 1977, Stevens et al., 1982, Alm and Hamre, 2001) using databases of the predominantly slender piles used by the oil and gas industry. Empirical methods that account for 'friction fatigue' or length effects and use in situ tests such as the CPT are convenient for capturing ground variability, both with depth and across large offshore sites, and can offer improved predictability. The most widely adopted SRD method in practice is that developed by Alm and Hamre (2001). Internal and external shaft resistance are not considered separately and in sands, τ_f is calculated as a function of the total CPT cone resistance, q_t, the relative distance of a given soil horizon above the pile tip, h, and the effective overburden pressure, s'_{vo}:

$$\tau_f = 0.00264\, q_t \left(\frac{\sigma'_{vo}}{p_a}\right)^{0.13} \sigma'_{vo} tan\delta' + \left(0.01056\, q_t \left(\frac{\sigma'_{vo}}{p_a}\right)^{0.13} \sigma'_{vo} tan\delta'\right) e^{-\frac{\sqrt{\frac{q_t}{\sigma'_{vo}}}}{80}h} \qquad (2)$$

where δ is the sand-pile interface friction angle. At the base in sands, $\mathrm{q_{ba}} = 0.15\mathrm{q_t}(\mathrm{q_t}/\sigma'_{\mathrm{vo}})^{0.2}$. The method is based on a database of 186 slender piles with diameters of 0.76-2.74m with a mean of 2.24m and a standard deviation of 0.39m and slenderness ratios of 14.4-40.8 with a mean of 25.3 and a standard deviation of 7.1. One pile in the database has an *L*/*D* ratio of 151. The formulation of the Alm and Hamre approach makes extrapolation to the emerging OWT pile geometries uncertain; equation (*2*) does not include a diameter term within the degradation function, likely due to the relatively uniform database employed. Recent studies have highlighted the need for new approaches to predict pile driveability for larger diameter piles Perikleous et al. (2020) assessed the performance of several empirical methods, including the Alm and Hamre (2001) approach, against installation records of 260 North Sea monopile foundations and found poor prediction accuracy. Maynard et al. (2019) back analysed 202 monopile driving records for piles installed in a range of ground conditions and found variable results, with significant over-prediction using the Alm and Hamre (2001) for the sands and clays at two out of three sites. They proposed empirical fitting parameters to resolve the differences between their observations and the results obtained with the Alm and Hamre (2001) method.

CPT-based static axial design methods, intended to predict medium-term pile capacity, have gained popularity in recent years and have been used in SRD predictions with variable success (see e.g. Byrne et al., 2012, Schneider and Harmon, 2010). Lehane et al. (2020) describe a new 'unified' method to predict axial pile capacity in sands which draws together the four CPT-based methods recommended in API (2014). For full-scale (D>1m) circular offshore pipe piles in compression, at a time of two weeks after installation, the shaft friction is calculated from:

$$\tau_f = 0.0125 q_c \left[\max\left(\frac{h}{D}, 1\right)\right]^{-0.4} \left[1 - \left(\frac{D_{\mathrm{i}}}{D}\right)^2\right]^{0.3} \qquad (3)$$

Where q_c is the uncorrected cone resistance. The base pressure applied over the pile's gross base area, q_{bg}, is taken as $0.15q_{c,\mathrm{avg}}$ where $q_{c,avg}$ is the cone resistance within a zone extending 1.5D above and below the tip. The unified database consisted of static load tests on 71 piles (31 closed-ended and 40 open-ended) in siliceous sand. The open-ended piles in the database have diameters of 0.34-2m with an average of 0.66m and a standard deviation of 0.32m and an average *L/D* ratio of 28.9 with a standard deviation of 14.22. Two piles(at Mobile Bay (not shown on Figure 1) had diameters of 0.32m and penetrations of 42.4m giving L/D ratios of 132.5.

Figure 1 illustrates the spread of *L/D* ratios and penetrations for the Alm and Hamre (2001) and Lehane et al. (2020) unified sand databases as well as typical monopile and jacket pile geometries used to support OWTs. Current OWT jacket piles have L/D ratios that lie at the lower end of the Alm and Hamre (2001) calibration space and are well outside the static database ranges. Monopile foundations can be seen to fall outside of the parameter space of both the SRD and axial methods. The static formulation has the benefit that (i) it follows established physical mechanisms that are supported by observations obtained in instrumented pile tests (Lehane et al., 2020) and (ii) it accounts for pile scale in the formulations, through inclusion of a diameter term, allowing extrapolation to different geometries. While the axial static design method appears more flexible, there are three main obstacles to using the method in its current form to calculate SRD: (i) the long-term static pile capacity was calibrated for fully equalised or aged piles and is therefore likely higher than the SRD, (ii) both the ultimate pile tip movement and the behaviour of the internal soil plug during a static test is expected to be different to that induced during driving, and (iii) the underlying databases, while carefully collated and curated, are limited to particular ground conditions and pile geometries (there are no available data for piles with D>2m).

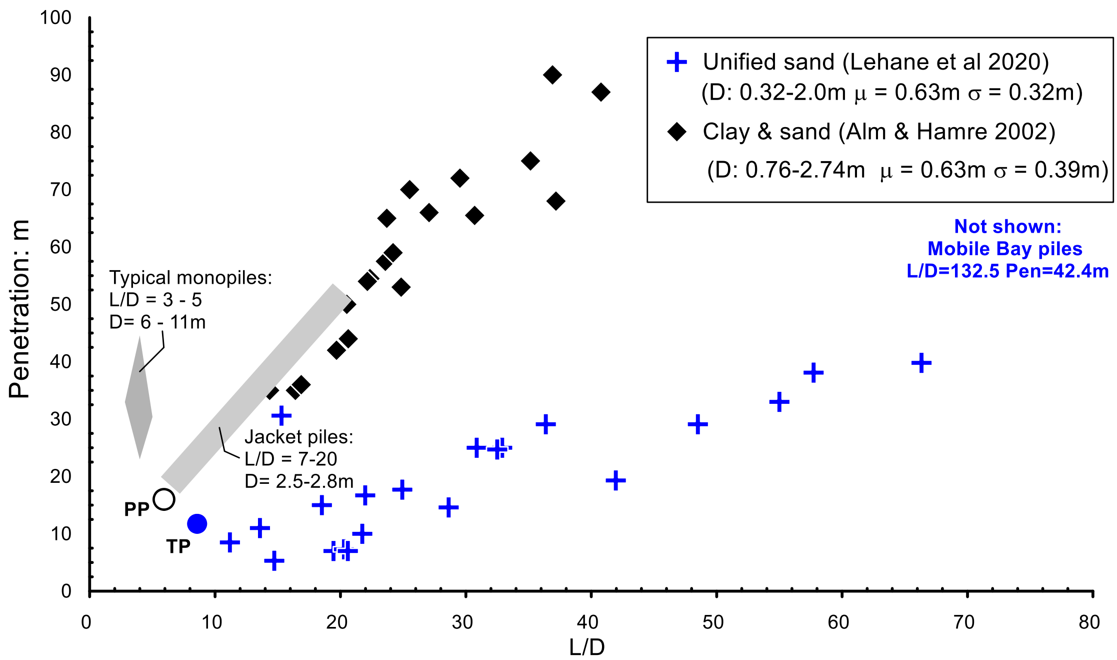

Figure 1 Parameter space of currently available method to predict SRD (Alm and Hamre, 2001) and static axial capacity of open ended tubular piles in sand (Lehane et al., 2020) with typical monopile and jacket pile geometries presently used to support OWT.

Given the large-scale nature of next-generation offshore wind farms (OWF), considerable savings can be realised if a more optimal, automated and adaptive approach to pile installation prediction at OWF sites is adopted. The aim of the iDRIVE project was to develop an optimisation framework which can be used to update uncertain model parameters in the axial static design method for the prediction of pile driveability. The optimisation process was undertaken using a robust Bayesian approach to dynamically update uncertain variables during driving to improve predictions. The approach was demonstrated using a previously published case study from a German offshore wind site.

RESEARCH AIMS & OBJECTIVES

The iDrive project aimed to achieve a step-change improvement in the reliability of monopile driveability predictions helping to reduce uncertainty and capital costs by developing a robust statistical framework for predicting the soil resistance to driving (SRD). The specific aims included:

Aim 1: Develop an intelligent forecasting approach for offshore monopile driveability.

The first objective was to develop an intelligent framework to autonomously optimise pile driveability predictions. The goal was to update uncertain input parameters of a cone penetration test (CPT)-based SRD model using robust Bayesian machine learning (ML) techniques to dynamically update these variables during a drive.

Aim 2: Application to real-world world OWF installation data.

To establish proof of concept, the second aim was to evaluate the developed tool using real-world installation data provided by industry partner Vattenfall. A secondary goal was to ensure that the intelligent prediction tool was developed in a form that is compatible with the records typically collected in industry such that it is suitable for industry take-up and impact.

SUMMARY OF PROGRESS

Phase 1: Dynamic driveability analysis using generalised CPT-based SRD models

The driveability calculations were performed using the IMPACT program (Randolph, 2008) which employs the method of characteristics (De Josselin de Jong, 1956) as a numerical method. The shaft resistance is modelled at each node along the pile length using linear springs and a plastic slider (see Figure 2), representing the relative movement between the pile and the soil and the static shaft resistance respectively. A dashpot is also included which accounts for all soil damping effects.

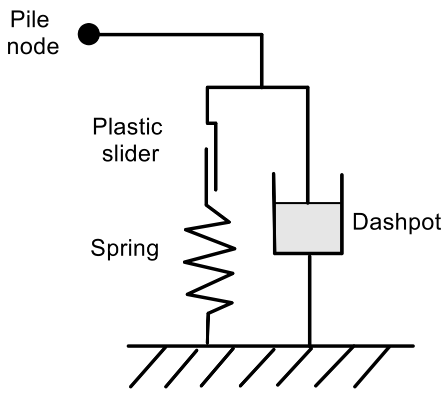

Figure 2 Traditional soil resistance models; adapted from Smith (1962)

While IMPACT uses the Smith (1962) approach to model the soil resistance, an estimate of the shear stress, τ_f, along the pile length and the end-bearing must be first determined using an empirical SRD model. The iDRIVE project adopted a generalised deterministic SRD models using the form of the static axial design method described previously:

$$\tau = a_{s1} q'_{t} \left[\max\left(\frac{h}{D}, a_{s2}\right)\right]^{-a_{s3}} \left[1 - \left(\frac{D_i}{D}\right)^2\right]^{a_{s4}} \qquad (4)$$

where a_{s1}, a_{s2}, a_{s3} and a_{s4} are model parameters. For consistency, q'_t is adopted in place of q_t, where q'_t is the total cone resistance less the hydrostatic pore water pressure, u_0. Consistent with the static formulation for sands, the base pressure is taken as equal to $b_s q'_{t,avg}$ (Eq 5) where $q'_{t,avg}$ is the cone end resistance averaged 1.5D above and below the pile toe, and applied over the full gross base area of the pile.

Phase 2: Development of an intelligent framework for SRD model updating

For equations (4) and (5), the greatest uncertainty relates to the soil penetration resistances; the SRD model input parameters are therefore treated as uncertain variables to be updated sequentially during driving as shown in Figure 3. The vector of uncertain variables, $\boldsymbol{\theta}$, can be defined as:

$$\boldsymbol{\theta} = [\, a_{s1}, a_{s2}, a_{s3}, a_{s4}, b_s] \qquad (6)$$

The recommended empirical values given previously (see Eq (3)) are taken as the best prior estimate of $\boldsymbol{\theta}$. A default coefficient of variation (COV) of 0.3 has been adopted for all parameters in $\boldsymbol{\theta}$.

The developed model can be defined as:

$$\boldsymbol{y} = g(\boldsymbol{\theta}) + \varepsilon \qquad (7)$$

where $\boldsymbol{y} = [y_1, y_{2,\ldots,} y_n]$ is the vector of calculated penetrations per blow corresponding to strokes $\boldsymbol{x} = [x_1, x_2, \ldots, x_n]$, n is the number of observed data points used for Bayesian updating, $g(\boldsymbol{\theta})$ denotes the IMPACT calculated penetration per blow using the soil resistances defined by equation (4) and (5), and ε is a noise term that captures the model and measurement errors.

The prior lognormal distributions of the model input parameters are updated to account for the data ***y***, using the likelihood function $p(\mathbf{y}|\boldsymbol{\theta},\mathbf{x})$, to produce 'posterior' distributions of **θ**. The likelihood function describes the probability of predicting the observed driving data using the existing model for particular values of the parameter vector **θ**:

$$p(\boldsymbol{y}|\boldsymbol{\theta},\boldsymbol{x}) = \prod_{\mathrm{i}} p(y_{\mathrm{i}}|\boldsymbol{\theta},\boldsymbol{x}) \tag{8}$$

The posterior distribution of the model parameters, $p(\boldsymbol{\theta}|\boldsymbol{x},\boldsymbol{y})$, is obtained using Bayes' theorem as follows:

$$p(\boldsymbol{\theta}|\boldsymbol{x},\boldsymbol{y}) = \frac{p(\boldsymbol{y}|\boldsymbol{\theta},\boldsymbol{x})\, p(\boldsymbol{\theta}|\boldsymbol{x})}{p(\boldsymbol{y}|\boldsymbol{x})} \tag{9}$$

$p(\boldsymbol{y}|\boldsymbol{x})$ in equation (12) normalises the joint posterior distribution to ensure that it integrates to one and is obtained by marginalising out ***θ*,** as follows:

$$p(\boldsymbol{y}|\boldsymbol{x}) = \int p(\boldsymbol{y}|\boldsymbol{\theta},\boldsymbol{x})p(\boldsymbol{\theta}|\boldsymbol{x})d\theta \tag{10}$$

The gradient-free sequential Monte Carlo (SMC) sampling technique was used to perform Bayesian inference. The SMC method recasts the posterior distribution given by equation (11) as follows:

$$p(\boldsymbol{\theta}|\boldsymbol{x},\boldsymbol{y})_{\mathrm{SMC}} \propto p(\boldsymbol{y}|\boldsymbol{\theta},\boldsymbol{x})^{\beta} p(\boldsymbol{\theta}|\boldsymbol{x}) \tag{11}$$

where β is the 'tempering' parameter such that $\beta = 0$ recovers the *prior* and $\beta = 1$ recovers the *true posterior*. The parameter β therefore allows tuning of the sampling by incrementally introducing the importance of the likelihood function. This framework was developed using PyMC3 programming in Python 3.6.

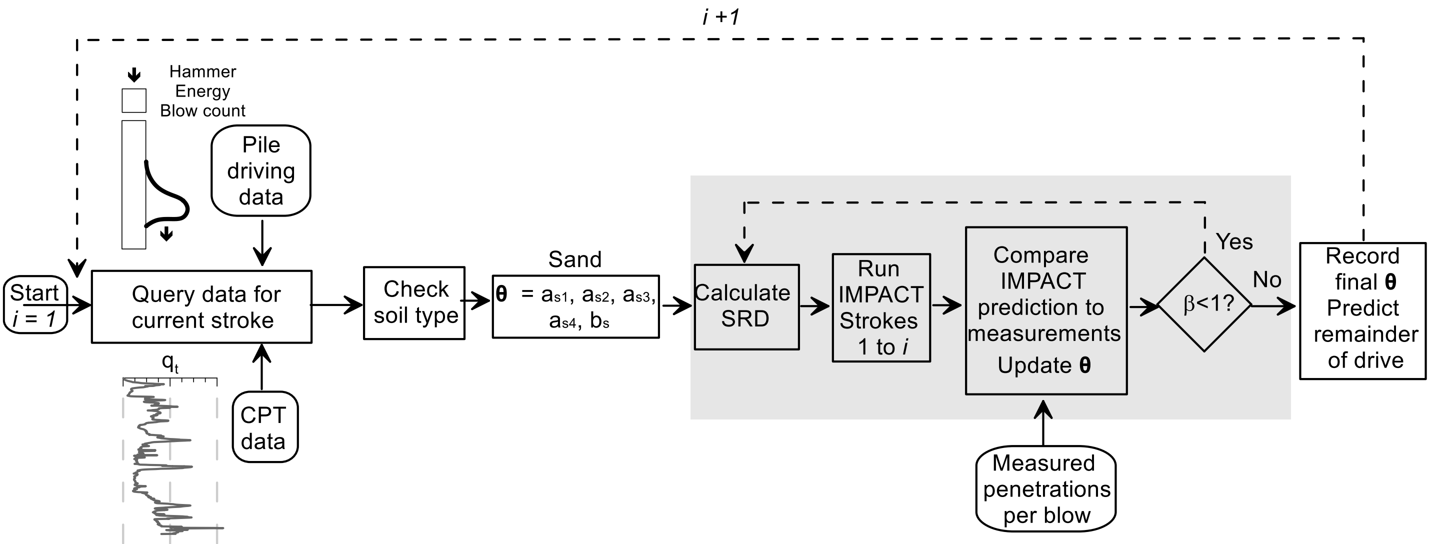

Figure 3 Model parameter updating framework (β is the tempering parameter as described in equation (11))

Phase 3: Real-world application

The developed approach was validated using real-world installation data from a German offshore windfarm provided by industry partners. The case study focuses on driving of the 1.37m diameter

(L/D=8.6, diameter-to-wall thickness (D/t) ratio=34) steel pipe 'pre-construction' test piles (TP) and 2.7m diameter 'production piles' (PP) (L/D=5.9 D/t=53) at two wind turbine generator (WTG) locations. The first optimisation involved updating the default prior parameters from Lehane et al. (2020) using measured installation data from TP WK38-3 (D = 1.372 m), the only pile installed without dynamic monitoring. This pile represents a typical dataset of an unmonitored OWT foundation pile. The performance of the optimised parameter set from this 'prototype' pile was assessed by performing unseen calibrations on identical piles WK38-1 and WK38-2, which benefit from close proximity to the optimisation pile. The second optimisation involved updating the same default prior parameters, this time using measured installation data from the larger diameter PP (D = 2.7m). Unseen calibrations are subsequently performed on three additional identical PPs at the same location. The adopted framework is illustrated on 4.

The difference between measured and SMC-predicted driveability calculations are compared with those determined using the prior parameters for three additional identical production piles at the same location in Figure 5. Calculations determined using the industry-standard Alm & Hamre (2001) approach have also been included. The results obtained using the SMC optimised parameters show very good predictions of the penetrations per blow giving confidence in the adopted parameters and methodology.

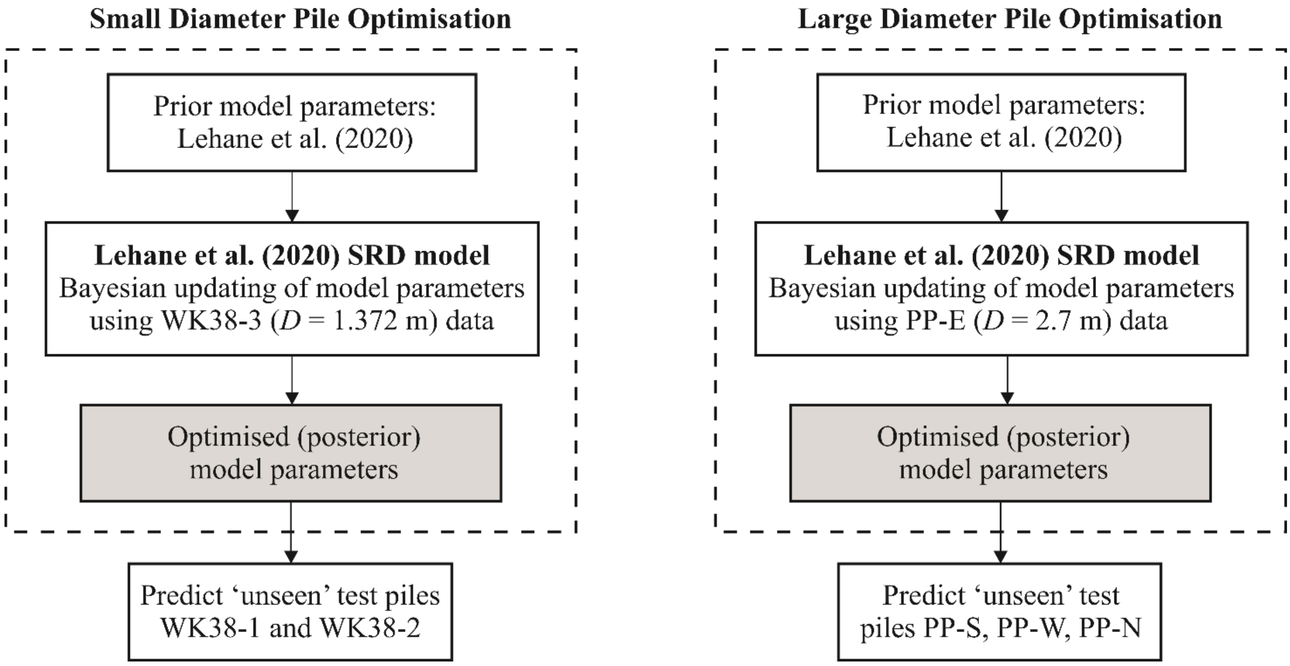

Figure 4 Illustration of adopted framework for optimisation of SRD model parameters based on pile installation data from TP and PP

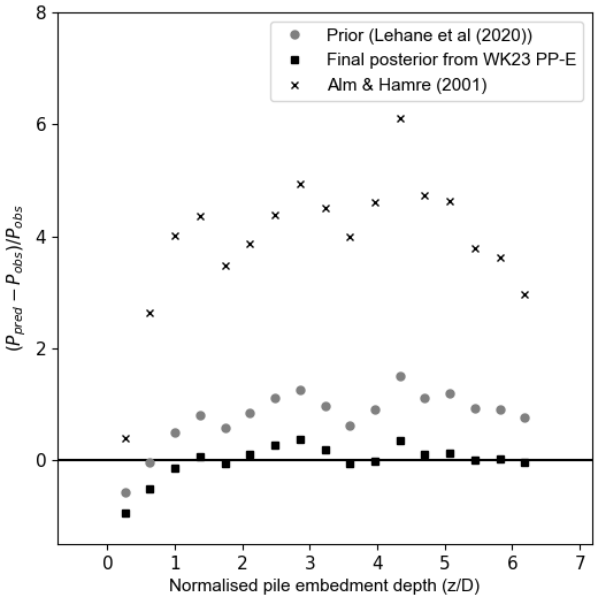

Figure 5 Comparison of model predictions of pile driveability for an unseen verification PP pile

OUTCOMES

(a) The iDRIVE team have developed a new tool to forecast pile driveability for use in industrial practice. We are currently working with industry partners to deploy the developed research more widely.

(b) A conference paper has been submitted summarising the probabilistic CPT-based approach to pile driveability.

(c) A journal paper has been submitted summarising the work described above.

(d) A second journal paper is planned to summarise a complementary to use an artificial neural network simulator in lieu of the IMPACT software programme to achieve a computationally light implementation.

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