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Prediction Of Bearing Pressure Of Isolated Square Footing Resting On Layered Soil Using Artificial Neural Network (Ann) Technique

Bilal Yousaf
Department of Civil engineering
University of Engineering and Technology
Peshawar, Pakistan
engr.bilal.yusuf@gmail.com

***Abstract*—This research is based on creating a machine learning Artificial Neural Network (ANN) model which can efficiently predict the bearing capacity of isolated square footing lying over the layered soil: clay over sand. In practice, the geotechnical engineers often use an empirical, analytical, correlations and experimental methods for ultimate soil bearing pressure which are assumption oriented, time consuming, site specific, mismatched simulation and costly. The total of 108 cases were analyzed in FEM based Plaxis 3D for various soil profiles. Onward, the MATLAB software has been used for developing ANN model by feeding the dataset into 70% training and 30% (validation and testing) to predict ultimate bearing pressure of soil. Finally, the optimal 5-7-1 neural network with a co-efficient of determination (R^2) equal to 0.991 is selected as best fit AI model of the bearing capacity for layered soil: clay overlying sand. This study can be further extended to other shapes or sizes of footing, soil pattern and AI algorithms.**

Keywords—Bearing Capacity, Layered Soil, Plaxis 3D, MATLAB, Artificial Neural Network.

I. INTRODUCTION

In reality, a natural soil deposits with homogenous properties seldom exists [2][9]. The computation of bearing capacity of a soil is vital part of foundation design which determine the maximum load of shear failure of soil, experiencing from super-structure and optimize the foundation cost. The majority of revolutionary researches had considered the soil as homogenous infinite mass with isotropic properties like Prandtl [42], Terzaghi, Meyerhof [7], Vesic and Hansen which may not be applied to layered or stratified soil with varying properties with depth in actual. So, there is a difficulty of obtaining true bearing capacity in state of stratified soil. The bearing capacity can be affected with shear strength parameters, size/embedment of footing in soil and thickness of upper layer.

Although, the solutions presented for multi-layer soil are based on model testing, empirical or analytical approaches i-e Limit equilibrium method, kinematic approach (limit Analysis) and slip analysis for finding bearing capacity i-e Button [10], Reddy & Srinivasan [25], Brown & Meyerhof [11], Meyerhof [12], Hanna & Meyerhof [13][14], Das [15], Purushothamaraj et al. (1974), Michalowski & Shi [22] and Oda & Win [24].

In order to cope with the problem; wherein, the large physical dimension of foundation i-e raft, pavements, storage tank etc affects the multiple layer requires a robust and accurate computation of the soil behaviour to avoid hazards.

The FEM software has more benefits than experimental model testing due to efficient and easy controlling the variations of various parameters and studying stresses which is difficult if we do in model testing [20][26]. Generally, the analytical/empirical solutions or correlations from lab testing are site specific with margin of error in simulation while the experimental load tests are time and cost consuming exercise [16]. So, the FEM software models the complex soil behavior and discretize it into small elements controlling its non-linearity and mixed boundary conditions.

In addition, the AI has immensely gained attraction of researchers to make the systems capable of performing tasks which typically require human thinking. It can be successfully applied to every geotechnical engineering problem. As, the behavior of shallow and deep foundation is uncertain and complex which brought AI in action to resolve such intricacy [36]. The essence of AI is that input and output data are guided to system in order to note the functional relationship, even the physical behavior is hard to elaborate. However, the AI system does not assume itself but use the guided data to develop their structure and system for simulation of physical behavior. The AI not requires beforehand any knowledge of non-linearity, as common in simple statistical regression analysis which staggers in processing highly complex and non-linear problems.

In this study, the PLAXIS 3D has been used to compute the ultimate bearing capacity for various soil cases, footing geometry and thickness ratio as defined in Figure: 1. Later on, the results were used for development of ANN model.

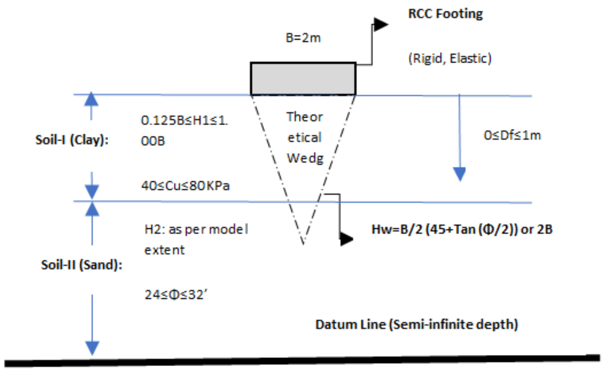


Fig. 1: Schematic Problem Diagram

II. PREVIOUS STUDIES

The past researches of 19th Century suggests the solutions for layered soil based on lab model testing, semi-empirical/analytical equations and theoretical approach i-e Terzaghi (1943), BUTTON (1951), Meyerhof (1974), Meyerhof & Hanna (1980). They focused on strip footing, homogenous soil, lab testing, and for layered soil profile brought concept of strong-weak layer and weak-strong layer which provides equation based on punching shear and soil squeeze effect. Most of cases analyzed for sand overlying clay rather clay over sand. As per Meyerhof (1974), if qt>qb, the effect of punching shear from first layer transfer to second layer. In such case, the max bearing capacity shall be equal to qt. Apart, if qt<qb, the lower layer becomes rigid base and soil squeezes laterally between footing and rigid base; thus, the max bearing capacity should be equal to qb.

In recent years, Finite Element Method (FEM) has been utilized mostly in geotechnical engineering for accurate simulation and analysis of complex geotechnical problems [16-19]. (Zenon and Katarzyna, 2006) had investigated the 04 cases of layered soil using PLAXIS 3D and compared result with traditional terzaghi equation. A flexible strip and square footing laid on Two-layered Phi-C soil assuming no effect of W.T which were analysed for bearing capacity for range $0 \leq h_1/B \leq 2$ under concentric loading in PLAXIS 3D for validating the method of average strength parameters suggested by Purushothamaraj et al. (1974). It was found that Qu decreases for clay over sand case and vice versa w.r.t H/B.

(Mosadegh & Nikraz H, 2015) had numerically investigated bearing capacity of strip footing on clay overlying sand using ABAQUS, and compare with terzaghi equation shows that the dilation angle given by FEA is quite significant in predicting bearing capacity of two-layer soil. They also found that the bearing capacity decreases with adding clay layer to sand layer with different upper layer thickness. They used B=3m and H/B=0 to 2. They further reported that FEM is a powerful tool which provides comfort for designers in finding Bearing capacity. The experimental methods are time consuming and complicated as limited equilibrium.

(Mandeel et al. 2020) performed a numerical modelling on PLAXIS 3D for find a bearing capacity of layered Soil. They selected stiff clay, soft clay, medium sand and dense sand for analysis. The key input parameters included: Upper layer thickness H/B=1-7m, cohesion (C_u), friction angle, Dilation angle and footing width (B=3 & 6m) which were varied to study their impact on the bearing capacity related to layered soil. The controlled prescribed displacement method was utilized which stops the load-settlement curve at reach of S=0.1B. The multiple regression analysis also performed to find the important variables influencing bearing capacity.

(Ramadan and Hussien 2015) have studied the effect of strip footing under vertical load on two layers soil system (sand overlying clay) using FEA software PLAXIS 3D. The experimental (Model testing) and numerical work (PLAXIS 3D) were performed which has shown that upper layer thickness and strength affects the bearing capacity. Also, the PLAXIS 3D was ranked as convenient and reliable tool for analyzing bearing capacity of two layered systems.

(Acharyya et al. 2018) had conducted a study to determine failure mechanism and AI models for predicting bearing capacity for square footing resting on crest of Phi-C soil slope. The footing was modelled and analysed in PLAXIS 3D, validating experimental work of sq. footing on sloppy ground by Castelli and Lentini (2012). The effect of set-back distance (b), footing width and embedment depth on bearing capacity were inspected. The model with 10 numbers of neurons in the hidden layer proved to be the 'best' model for the 7-10-1 ANN architecture to obtain the ultimate bearing capacity. However, it is not applicable to different shape footings, multi-layer soil and adjacent depth footing.

(Shahin et al. 2002; Shahin et al. 2003; Shahin 2015) provided an overview of AI in the geotechnical engineering. It has been reported that the ANN is better than conventional approach in performing regression tasks for prediction of bearing capacity and settlement of spread footing. They also provided that there is no specific rule for selecting the number of neurons. The selection is trial and error method. The best performing model would be decided on the basis of R^2 and MSE. The common division of dataset involve 70% training and 30% validation cum testing. However, there is still no specific formula for division. The data must be pre-processed to avoid uncertain behaviour of neural network. The normalization ensures proper handling by activation functions i-e sigmoid, TanH and relu while transferring the weights or data signals.

(Jaafar et al. 2008; Kuo et al. 2009; Behera et al. 2013) utilized experimental data for strip footing resting on soil for developing AI (ANN) model to evaluate geotechnical behavior on layered soil (clay overlay sand). Multi-layer cohesive soil was selected for analyzing bearing capacity using multiple regression methods (MRM) and multiple layer perceptron (MLP). ANN outperformed the method of Multiple regression analysis and bowles (1997). Further shown that B.C increase with increasing cohesion and footing width. AI techniques perform better than, or at least as well as, the traditional methods used as a basis for comparison.

(Nazir et al. 2014) had developed an ANN model for predicting bearing pressure of spread footing. They used 75 axial compression tests of spread footing on sandy soil as input for ANN architecture. The data was divided into 70% training, 15% Testing and 15% validation. There were six inputs (B, L, D, ϕ, σ') and one output (Qu) as predictive parameters. They analyzed the performance of models by changing number of neurons. The model with 8 neurons has performed well and opted as best fit model for prediction of bearing capacity. The Levenberg–Marquardt (LM) learning algorithm due to its efficiency for training networks has achieved co-efficient of determination (R^2) value of 0.98 for ANN model. It is reported that the one hidden layer is enough to develop satisfactory model. Although, the increase in hidden layers can be done if the model performance is not improving. Despite, it is suggested to not increase number of hidden layers than inputs.

III. PLAXIS 3D MODELLING & ANALYSIS

It is essential to define the soil types, parameters, characteristics and defining layers prior delving into analysis. Most of the previous researchers had defined soil type, properties and layer arrangement utilizing the available literature [41][33][28][26].

A different type of soil along with essential parameters have been taken for analysis of bearing capacity. The parametric properties of various soil types are being selected from available literature of renown authors i-e Bowles (1996) and Das (2010), illustrated below:

Soil Type	Symbol	Cu (KPa)	Φ	γ (KN/m^3)	E (MPa)	ν
Medium Clay	MC	40	0	16	16	0.35
Stiff Clay	SC	60	0	18	42	0.35
Very Stiff Clay	VSC	80	0	20	80	0.35
Medium Dense Sand	MDS	0	24	18	18	0.30
Dense Sand	DS	0	28	19	26	0.30
Very Dense Sand	VDS	0	32	20	40	0.30

Table 1: Soil Types and Properties

The cases for research were being selected as different to avoid repetition of work of previous researchers and addressing areas where the work is actually required. The total of 108 cases were being opted for analysis in FEM software i-e Plaxis 3D in order to study impact on bearing capacity due to varying width of footing, footing depth, change in UL thickness (H_1), and strength parameters of both layers. For 2m footing width (B), total of 108 cases were being analyzed including 54 cases each at Df=0 and Df=1m. The selected combinations and cases are illustrated below:

H_1/B	Soil-I	Soil-2
0.125	MC, SC, VSC	MD, DS, VDS
0.250	MC, SC, VSC	MD, DS, VDS
0.375	MC, SC, VSC	MD, DS, VDS
0.500	MC, SC, VSC	MD, DS, VDS
0.750	MC, SC, VSC	MD, DS, VDS
1.00	MC, SC, VSC	MD, DS, VDS

Table 2: Cases for Analyses

The model dimension was selected with care, so as to avoid intersection of boundary and elastic stress isobar of boussinesq's (stress applied till failure). (Ramadan et al. 2021) had selected the model dimension as 40 times in (x) direction,15 times of (y) and 5 times of (z) direction of footing width. (Mosadegh & Nikraz H 2015) had selected dimension in X-Y direction as 12 times of footing width and depth of 7 times of width. As the 0.1q for square footing occurs at 2B in vertical and 1B in horizontal (Bowles, 1996). Thus, on a safer side, I had fixed dimensions as 10 times in all X, Y and Z direction to prevent the effect of confinement from the boundaries and ensure accurate results.

For model element, 10-Noded Tetrahedral element is used due to its efficient stress transfer and accuracy for geotechnical problems. This function works in meshing phase of model which explode the complete model in finer to coarser elements. The same 10-Noded Tetrahedral element is used by (Acharyya et al. 2018).

The footing is modelled defined as "plate" with material properties of Linear elastic Model and rough base to avoid horizontal displacement. The material is used as RCC of Grade: M-20 whose Modulus of Elasticity (E) is calculated using ACI 318-19, Section 19.2.2.1 formula: E= 4700*sqrt (fc') [43]. The LEM consist of E and ν value.

The linear elastic perfectly-plastic Mohr-Coulomb model is used for simulating soil which consists of five input parameters, i.e. Elasticity (E and ν), Plasticity (φ and c) and angle of dilatancy (ψ). The dilatancy angle has been determined as per Plaxis 3D- Tutorial Manual (2024) which provides that clays mostly have angle equal to zero while quartz sand has in magnitude i-e ψ= Ø-30.

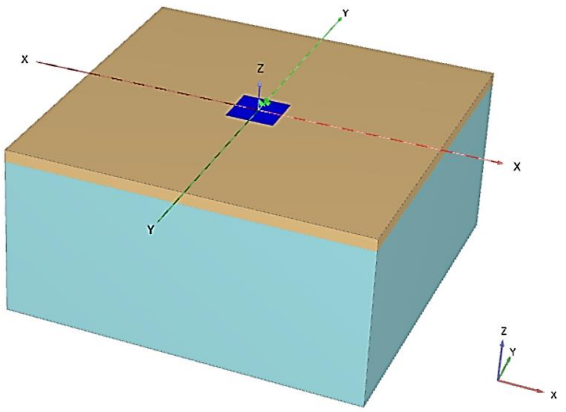


Fig. 2: Geometric Modelling

The input parameters for modelling material in PLAXIS 3D are demonstrated below:

Parameter	Clay	Sand	Concrete Footing
Material Model	Mohr-Coulomb	Mohr-Coulomb	Linear Elastic
Material Behavior	Un-drained (B)	Drained	Non-porous
Cohesion, Cu (KPa)	40, 60, 80	0	-
Friction Angle, Ø	0	24,28,32	-
Young's modulus, Es (MPa)	16,42,80	18,26,40	21 x 10^3 (ACI-318, M-20 G)
Dilatancy Angle, ψ	0	2, 4, 6	
Poisson's ratio, υ	0.35	0.30	0.15
Unit weight, Ƴ (KN/m^3)	16,18,20	18,19,20	24 (RCC)
Interface Strength Reduction, R	-	-	1.00

Table 3: Input Parameters for Material Model

"Meshing" is the essential step which controls the accuracy of model results. In Plaxis 3D, there are five fundamental types of meshing options i-e Very coarse, Coarse, Medium, Fine and Very fine which may be modified with 'Mesh coarseness factor'. The mesh element should be arranged carefully, as too smaller or finer mesh increase calculation time and too large gives incorrect results. The medium mesh with coarseness factor of 0.2 is used for footing or nearby soil which is our main point of interest while the rest of soil mass is meshed as "medium" with factor of 1.00 to attain better results and avoid delay in processing. [23][27]

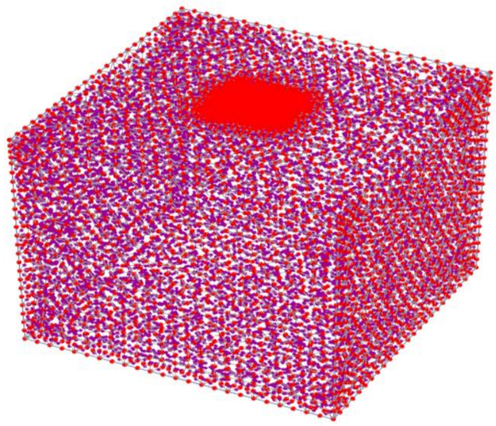


Fig. 3: Meshing and Connectivity nodes of Model

The model has been applied load until it gives clear failure peak of shear failure. The bearing capacity for 108 cases has been determined by generating load (per unit area)-settlement curve by virtue of built-in "curve" tool. After getting the plot, the two-tangent method as suggested by (Dewi et al., 2021; Terzaghi, 1943) was used to find the ultimate bearing capacity (Qu) of layered soil.

IV. ARTIFICIAL NEURAL NETWORK MODEL

The ANN model is developed using the methods and guidelines of past researchers. The most reliable approach has been selected to optimally design the AI network for efficient prediction of bearing capacity. The ANN is a supervised learning approach with having known input and output of problem for training the model. MATLAB was installed and utilized for developing ANN model.

MATLAB is a convenient, reliable and powerful computing software for researchers. In this study, ANN model has been developed using MATLAB. The software has "Neural network Tool" which handles the Data (input-output), splitting, build network, Training function, plots and model export for in-dept analysis.

Following steps followed for selection of best neural architecture model:

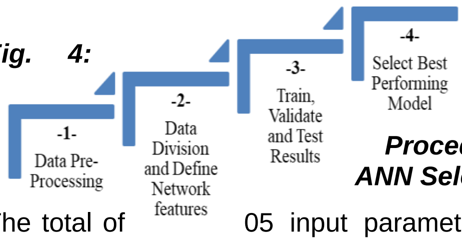


Fig. 4: Procedure for ANN Selection

The total of 05 input parameters i-e i-e D_f, B, H/B, C_{u1}, $Ø_2$ and 01 output i-e Q_u selected for developing ANN model. Similarly, the data was arranged in normalized from 1 to 108 cases to give proper weightage to each parameter.

The 70% data separated for training while 30% for (15%-Validation & 15%-Testing).

However, in MATLAB, there is a “Neural Network” tool which is automated in performing the various functions of artificial neural network. It has built-in feature of data division, setting learning algorithm, performance curves, input/ouput data. By default, the hidden layer size is selected as 1 which is quite satisfactory for training our model. Although, there is an option for changing number of nodes starting from 1 to any planned value. The learning algorithm is used as “Levenberg-Marquardt” which is also suggested by (Mishra et al. 2016; Acharya et Al., 2018 and Nazir et al., 2014). Das and Basudhar (2006) had reported that many nodes could lead towards memorizing while too less create problem in learning the data pattern. The general rule for selection is Nodes min: (i+o)/2; Nodes max: 2i+1.

The accomplishment of best network is possible only by a trial-and-error method. There is no specific equation to directly determine the best model as reported by previous researchers. So, the training of model was started with 01 hidden layer and varying the number of nodes ranging from 1 to 10. For each node, the network has been trained on certain epochs. Epoch is the rate at which the training data is passed in batches or whole through network for enhancing capability of learning, model generalization, reduce training loss and overfitting/memorizing.

The point at which there is no further possibility in reduction of MSE, the iteration was automatically stopped with validation set satisfaction, so as to avoid overfitting of model.

V. RESULTS AND DISCUSSION

A. Finite Element Modelling

A bearing capacity of 108 soil cases were analyzed for footing width (B) of 2m at Df-=0 and Df=1m and various soil combination, shown below:

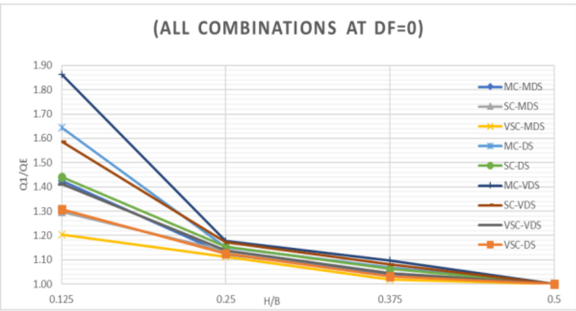


Fig. 5: Bearing Capacity ratio at Df=0

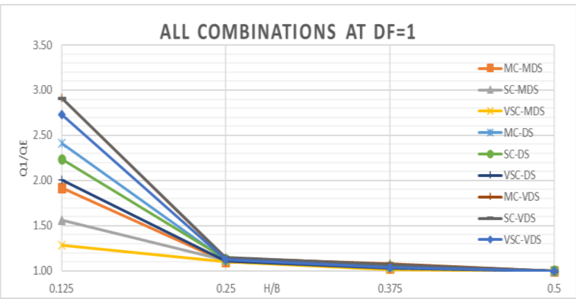


Fig. 6: Bearing Capacity ratio at Df=1m

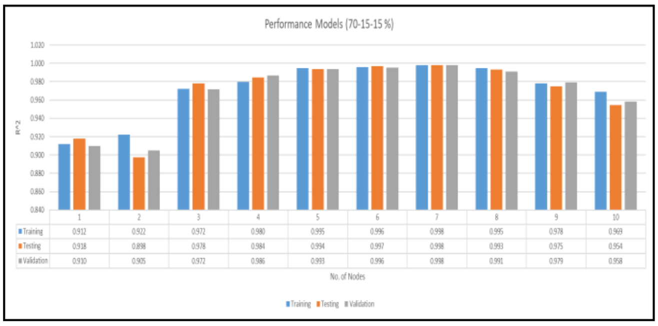
The two tangent method is used to find the ultimate bearing capacity of layered soil from the load vs settlement curve. The data record of 108 cases is onward used for development of neural network.

B. Neural Architecture

While, finding a best model of ANN in MATLAB, the number of neurons was varied from N=1 to 10 with a hidden layer size=1. The best model obtained at N=7 nodes due to its reasonable value of R^2, MSE, RMSE and MAE.

The performance models result is illustrated below:

Fig. 7: Different ANN models



	1	2	3	4	5	6	7	8	9	10
Training	0.912	0.922	0.972	0.980	0.995	0.996	0.998	0.995	0.978	0.969
Testing	0.918	0.898	0.978	0.984	0.994	0.997	0.998	0.993	0.975	0.954
Validation	0.910	0.905	0.972	0.986	0.993	0.996	0.998	0.991	0.979	0.958

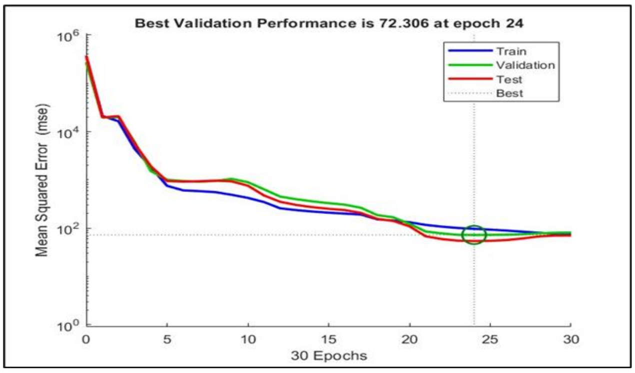


Fig. 8: MSE of 5-8-1 ANN Model

The bearing capacity predicted by selected ANN model 5-8-1 neural network is remarkable which yield results within close difference to bearing capacity obtain from Plaxis, as shown below:

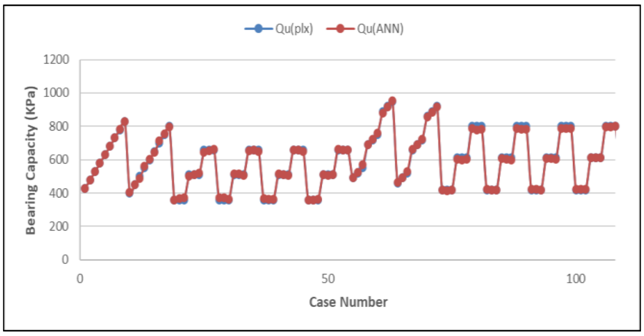


Fig. 9: Results Validation between Qu(plx) and Qu(ann)

VI. CONCLUSION

The ANN model was trained on dataset of 108 cases comprised of 5 inputs (B, D_f, H/B, C_{u1}, $Ø_2$) and 1 input (Q_u) using MATLAB, for prediction of bearing capacity for 2m isolated square footing on layered soil. The best and optimal neural network were found on 1 hidden layer and 7 no of neurons with having the accuracy parameter i-e R^2 value of 0.991 and 0.994 in testing and Validation. The MSE and error histogram also advocates the robustness and prediction accuracy of obtained 5-7-1 architecture network model. The predicted bearing capacity through developed ANN 5-7-1 network model is in good agreement to the Plaxis 3D bearing capacity.

The developed best performing ANN model can be deployed in real-world for predicting the ultimate bearing capacity of isolated footing laid over layered soil with certain limitations i-e footing size and soil type.

CONFLICT OF INTEREST

No conflict of interest

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