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Original Article

Artificial Neural Network-Based Prediction of Load-Bearing Capacity in Earthen Construction: A Comparative Analysis of Model Architectures In Morocco

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Abstract *- Earthen construction has been practised for millennia due to its availability, low embodied energy, and adaptability to diverse climates. In recent years, its resurgence has been driven by sustainability concerns and the need for eco-friendly alternatives in construction. However, predicting the structural performance of earthen materials remains a challenge due to their inherent variability. This study explores the potential of Artificial Neural Networks (ANNs) to enhance the understanding and prediction of load-bearing capacity in earthen structures. A comparative analysis of different ANN architectures is conducted, examining variations in network depth, activation functions, and training algorithms. Results indicate that optimally tuned, shallow networks outperform deeper architectures by minimizing computational complexity while maintaining predictive accuracy. This work demonstrates that data-driven approaches can improve the reliability and efficiency of earthen construction, offering engineers and architects valuable tools for sustainable building design.*

Keywords *- Artificial Neural Networks, Earthen construction, Load-bearing capacity, Machine Learning, Structural performance.*

1. Introduction

1.1. History

The use of natural materials, combining the use of invented homes and dwellings (Minke, 2009) [1], has been one of the primary needs for survival and creativity among mankind over the years (Adam, 1994) [2]. The date of the beginning of man's use of earth for construction is not clear (Forbes, 1965) [3], but examples of the use of this material can be found dating back over 9,000 years in the excavation of occupancy sites (Rosenberg et al., 2020) [4]. With the discovery of Göbekli Tepe (Yenigun, 2021) [5], Urfa has proven to be one of the oldest settlements in history and has been named "Zero Point of History" due to this feature, with more than 12,000 years of history (Dietrich et al., 2012) [6].

1.2. Types of Earth Construction

Adobe bricks: Adobe bricks (Medvey, B., & Dobszay, G., 2020) are produced with the help of stabilising agents such as bricks, mud and mortar. [7]. There are some significant benefits of sound insulation, including reduced levels of sound transmitted through walls, doubt and security: (Walker, K., et al., 2005) [8]. The use of such walls is also evaluated in the choice of the heating, ventilation and cooling systems (Kosny and Kossecka, 2002) [9]. Interpretation: The prepared samples reveal the fireproofness of the adobe bricks and their low energy investment in the raw materials (Ben Guida, 2015) [10]. Yet, the strength and stiffness of conventional adobes are not satisfactory, and their resistance to earthquakes is not significant; therefore, children and adults of these low-income groups are deprived of safe and durable housing in their everyday life (Silveira et al., 2012) [11].

Fig. 1 El Haj Yousif experimental school (E.A. Adam,2021) [12]

Rammed earth is a type of earth-based construction, where dry soil and water are mixed, then compacted in consecutive lifts within a formwork to create structures

(Maniatidis & Walker, 2003) [13]. Out of the several styles of earth construction, rammed earth presents the highest mechanical and structural strength due to the near-dry nature of the mixture and the formation through the compaction process (Bailly et al., 2024) [14]. The relevance of Rammed Earth (RE) remains significant today.

Earth construction is gaining increasing interest from builders and researchers seeking sustainable construction alternatives, driven by the rising environmental awareness within the construction industry (Abhilash et al., 2021) [15].

Fig. 2 Typical construction process of rammed earth walls (Adolfo Preciado and Juan Carlos Santos, 2020) [16]

Cob: clods of clay, subsoil, sand, and straw that are piled together to shape a monolithic wall (Hamard et al., 2016) [17]. When compared to conventional construction materials (bricks or concrete), cob has a far lower embodied energy, as this is primarily made from organic materials with little or no primary production processing, and its carbon footprint is much lower due to the use of local natural materials (Arduin et al., 2022) [18]. Moreover, cob is nonÃ• fatal and completely recycled, which tends to diminish the ecosystem destruction and the depletion of natural resources (Ranganath et al., 2024) [19].

Fig. 3 An external wall reveals the presence of cob bricks covered by straw (Enrico Quagliarini et al., 2010) [20]

Compressed Earth Blocks CEB: Modern earthen construction technologies represent the evolution of adobe, with the key difference being the compaction process. This process, which involves mechanical stabilization, results in a denser and more durable block(Losini et al., 2021) [21].

Fig. 4 CEBs Exposed to the natural environment (Aurélie Vissac and all,2018) [22]

Wattle and Daub: It is a composite building material for walls, where the "wattle" is the organic substructure made from materials like wooden strips, sticks, reeds, straw bundles, or small beams, with the weaving or binding method often understood through ethnographic analogy (S. Amicone et al., 2020) [23]. The same type of wet earth-straw mix is used in the cob technique, without any support or formwork. Plastic humps or loaves (cob is an old English word for loaf) of the mix are simply hand-packed layer by layer, forming monolithic and wide (50 to 80 cm) masonry walls (Henri Van Damme & Hugo Houben, 2018) [24].

Fig. 5 A lattice formed by weaving withies diagonally. South Cambridgeshire, c.1700 (Tony Graham,2004) [25]

1.3. Problematic

The main question under which this project falls is whether Artificial Neural Networks (ANNs) can be a prediction model for assessing CEB's mechanical performance. The difficulty is the limitation of conventional methods and the fact that conventional methods, such as physical assessment, can identify properties like compressive strength, durability and structural equilibrium. Although these traditional methods are reliable, they are usually time-consuming and expensive, and the need for specific equipment is not always available in a country such as Morocco

(Jayasinghe & Kamaladasa, 2007) [26]. The variability of locally available materials and the scarcity of standardised quality control procedures also complicate the manufacture and testing of CEBs (Walker and Standards Australia, 2002) [27].

In such a context, where cost and sustainability are critical, ANNs can be used to develop faster, cheaper and accurate predictions of the material performance (Miccoli et al., 2014) [28]. These challenges can be overcome by ANNs for a potential transformation of the use of CEBs in Morocco that provides a modern method of material design and contributes towards the promotion of eco-construction compatible with both local heritage and international sustainable development aims (Bui et al., 2009) [29]. In this framework, one may ask the following: How can Artificial Neural Networks (ANNs) be used to predict the mechanical behaviour of compressed earth blocks, and what can they bring more for earthen construction in Morocco?

Although CEBs are attracting more interest as a sustainable building system, their use has been limited due to the absence of computerized software tools to predict their mechanical behavior. However, a majority of the research undertaken to date is based on the testing of the physical properties for compressive strength and durability measures and the like, which are both expensive and time-consuming in terms of the amount of work and the specialized testing equipment required [30]. These types of constraints have a particular influence in the region, such as Morocco, where, in many cases, construction materials are locally produced and quality control is less uniform. Furthermore, little research has sought to employ numerical routines that could predict the performance of a material given a soil type, stabilizer or environmental influence. This lack of knowledge has been a limiting factor for the production of enhanced CEB mixtures and a wider application in industry, particularly with regard to economic and sustainable formulations (Walker & Standards Australia, 2002) [31], and (Turco et al.,2021) [32].

Artificial Neural Networks (ANNs) offer a pertinent and state-of-the-art solution to this challenge. These models can adapt to discover intricate relationships in the data, and have been successful already in predicting the performance of materials in other civil and geotechnical engineering contexts (Jeremiah et al., 2021) [33], and (Zeng, Z., et al. 2022) [34]. For earthy materials, ANNs may reduce the dependence on full-scale laboratory testing by extrapolating mechanical parameters, like compressive strength, from a few input parameters, such as grain size, plasticity, and moisture content, concerning less detailed testing (Yuan et al., 2024) [35]. This methodology is particularly timely as the construction industry comes under increasing pressure to adopt more Sustainable construction methods, which minimize carbon outputs and minimize high-embodied resources. In the Moroccan cultural context, where earthen building corresponds to an environmental need and opens the way to reusing this material, incorporating ANN prediction models would stimulate a new generation of sustainable, affordable and eco-responsible buildings, using earthen materials (Bui et al., 2009) [36].

2. Methodology

In this work, after an introduction detailing that it is crucial to develop earthen construction in Morocco and the possible application of Artificial Neural Networks (ANN) in predictive modelling, a guideline using IMRAD is adopted to evaluate the potential of following ANNs configurations in predictive accuracy. Various models were proposed to predict the compressive strength of compressed earth block with FE parameters obtained with ABAQUS.

These configurations were refined by tuning hidden layers, the number of neurons, activation functions and learning rates. The comparative analysis offers novel insights on model performance, state-of-the-art architecture and perspectives on ANN-prediction to sustainable construction based on local materials.

3. Results

3.1. ANN State of the Art

Artificial Neural Networks (ANNs) have been widely applied in modelling complex, non-linear behaviour of soils, specifically when deterministic methods are restricted (Koopialipoor and Moarefvand in Civ Eng Infrastruct J 51:526 545, 2017). 2018) [37]. They have been successfully used to estimate the soil settlement, slope stability and bearing capacity under different loading conditions [38]. The capacity of learning from noisy or incomplete datasets is the main advantage of ANNs in the field conditions, where highly accurate measurements are rarely available (Sharma & Samui, 2021) [39].

Meanwhile, the applications of ANNs are spreading in a wide range of civil and materials engineering. Some authors have used them to predict the mechanical properties of construction materials like compressive strength, tensile behavior, and durability performance (Khan et al., 2022) [40]. Ahmad et al. (2020) [41] employed neural networks to predict the compressive strength of geopolymer concrete and reached a good match between prediction and experimental values. Similarly, Zhang et al. (2024) [42] studied the ANN's ability to predict the behaviour of stabilized soil bricks with respect to mixing proportions and curing conditions. Nevertheless, despite being advanced, very scanty work has focused on ANN modeling of CEBs from raw or slightly stabilized clay obtained by local soils in some countries, such as North Africa. Current investigations are mainly for cementitious materials (cement-based) or suppose the use of usual commercial mixes, which reduces their application for a vernacular material and/or sustainable construction situation

(Lang, G et al., 2019) [43]. In addition, simulated data, such as that in the form of finite-element output, has been incorporated into training datasets only rarely, despite the fact that simulations can capture internal distributions of stress and failure, which are not otherwise available in experiments [44].

The destructive physical tests still remain the mainstream for CEB performance characterization. This is an indispensable technique but it is time-consuming and expensive; it is also sensitive to discrepancies in suturing and setting (Teixeira et al., 2020) [45]. It also has a limited ability to detect internal stress paths or possible zones of failure. In addition, finite-element modeling (FEM) is a complementary approach that enables the ability to simulate load transfer and material response to adjustable conditions at the boundary \(Dhadse et al. 2021) [46]. Despite its potential, FEM-based ANN modeling is underdeveloped, while recent studies have indicated that coupling the simulation data together with machine learning could improve the prediction efficiency and decrease the necessity of comprehensive physical tests (Bekdaş et al., 2021) [47].

When situated in a wider field of ecology and sustainability where earthen construction is historically based and environmentally well-suited, this hybrid approach is also seen as a practical asset for developing more rapidly eco-responsible answers in housing. This is especially the case in Morocco, where there is an abundance of natural clay resources to establish sustainable and high-performance/low-cost earth construction systems in combination with intelligent prediction tools (Gomaa et al., 2023) [48].

3.1.1. The Present

Currently, almost 50% of the world's population lives in earth-based dwellings **(**Goodhew & Griffiths, 2011**)** [49]

Fig. 6 World map illustrating the worldwide use of earth construction (Johan Vyncke et al.,2018) [50]

The majority of earth construction is located in less developed countries; however, it can also be found in Germany, France, and even the UK, which has over 500,000 earth-based dwellings (Marsh and Kulshreshtha, 2014) [51]. Earth construction has seen substantial growth in the US, Brazil, and Australia, largely due to the sustainable construction agenda, where it plays a key role (Carlos et al., 2022) [52]. Countries that have established Earth building codes, such as Australia, have a significant number of rammed earth dwellings; in fact, rammed earth accounts for 20% of the building sector there (Giuffrida et al., 2019) [53]. Meanwhile, Peru has become a leader in anti-seismic earth-building standards due to its recovery efforts in high Andean villages affected by strong earthquakes, promoting reinforced earth buildings (Tarque et al. 2022) [54].

3.2. Artificial Neural Network

Artificial Neural Networks (ANNs) have become increasingly popular in civil engineering due to their ability to model complex and uncertain data through pattern recognition, mimicking the functionality of biological neural systems (Dave & Dutta, 2014) [55]. Essentially, ANNs consist of interconnected nodes or neurons arranged in layers. Each neuron processes input by calculating a weighted sum and then applying an activation function to generate an output. These outputs then serve as inputs for the next layer, ultimately producing a final prediction or decision. This flexible structure allows ANNs to effectively identify hidden patterns and relationships within diverse datasets (Abiodun et al. 2018) [56].

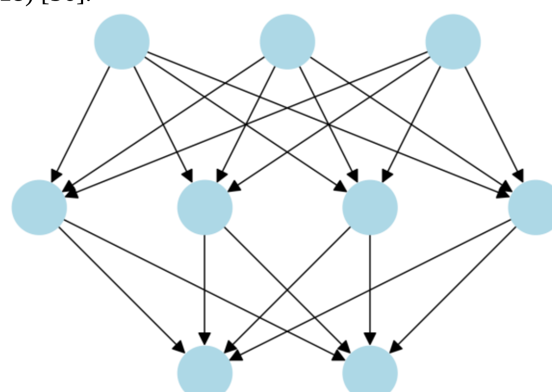

Fig. 7 Generic topology of an Artificial Neural Network, illustrating input, hidden, and output layers

One of the most significant properties of ANNs is their ability to process data on a large scale with high speed efficiency, especially if run on parallel computing machines. This control efficiency makes them particularly appropriate for handling the intrinsic challenges of complexity and uncertainties encountered in civil engineering (Izeboudjen et al., 2022) [57].

In structural engineering, ANNs have been effectively utilized in predicting structural responses such as load-carrying capacities and for structural health monitoring. For instance, ANN models have delivered a very good accuracy for predicting the ultimate strength of concrete-filled steel tubular columns over the traditional empirical approach (Amar et al., 2022) [58]. It has the advantage that it can take non-linear interaction between different structural factors into account.In geotechnical engineering, there are even successful applications of ANNs for modelling complex conditions such as soil response, foundation bearing capacity, and settlement variations [4]. Given their ability to deal with the often heterogeneous and nonlinear soil data, ANNs have always brought out better predictions than standard methods of regression (Shahin,2001) [59].

ANNs are commonly used in transportation engineering to predict pavement performance (such as pavement deterioration) and traffic operation. ANN lead to improved maintenance planning with the possibility of timely preventive actions, which contribute to cost savings and increase the service life of the infrastructure (Abambres, M., & Ferreira, A., 2017) [60].

In the field of material science, ANNs are often used to predict mechanical and durability properties of building materials. Recent investigations are underlining the high accuracy of ANNs in predicting the compressive strength of concrete, contributing to the design of mixtures which are ideal in terms of sustainability and cost (Chaabene et al., 2020) [61].

In addition, ANN has been widely applied to solve the realistic civil engineering problems, which includes predicting failure delays in construction projects (Yaseen et al., 2020) [62], cost estimation in construction project (Naif alsagr, 2023) [63], damage assessment for multi-story buildings (Bartkiewicz, 2000) [64], demand destruction risk in collusion (Adeusiewicz, 2000) [65], energy consumption in residential buildings (Runge, J., & Zmeureanu, R. 2019) [66], financial health of construction companies (Qamar & Zardari, 2023) [67].

3.3. CASE Study

Artificial Neural Networks (ANNs) are increasingly being used to predict engineering behaviours, particularly in the field of material properties and structural behaviour. They must correctly predict load-carrying capacity in earthen construction, often by compressed clays. Traditional methods for prediction, such as linear regression or parametric fitting, cannot be successful on materials such as compacted clay. This treatment usually presumes linearity and independence of variables, features that are not usually present in earth-based construction, where physical behavior is often dependent simultaneously on several factors, including geometric, mechanical and boundary parameters. In comparison, artificial neural networks can learn such complexity without the need for a priori defined mathematical relations and are therefore more appropriate for materials exhibiting nonlinear, homogeneous responses. Here, we explore how ANN architectures impact predictive accuracy and generalization.

In the current study, the finite element analysis is conducted through ABAQUS (Figure 8), in an attempt to model the compressed clay bricks with different widths and loads. Clay brick simulations were based on a physical sample collected in Morocco's Fez area, so the simulation replicates local specific material properties. The mechanical input of these simulations was based on the characterization of some undisturbed natural clay samples taken in the Fez (Morocco) area. This was a deliberate choice, as the area is still a repository of traditional mud building know-how. The combination of these values maintained model outputs in the realm of realistic, field-applicable scenarios..

The key parameters included:

Table 1. Parameters and variation ranges used in the study

Parameter	Unit	Variation Range/Value
Width	mm	200 mm – 230 mm
Load (Surface Load)	MPa	0.15 MPa – 1 MPa
Output Variable	mm	Displacement (calculated in mm)
Density	kg/m³	1800
Yield Stress	MPa	3.5
Plastic Strain	-	0
Young's Modulus	MPa	803
Poisson's Ratio	-	0.37

Output Variable:

- Displacement in mm.

The objective is to:

- Compare ANN architectures with varying numbers of hidden layers and neurons.
- Assess the impact of different activation functions (tansig, logsig).
- Optimize learning rate and data splitting ratios.
- Determine the best-performing ANN configuration for this dataset.

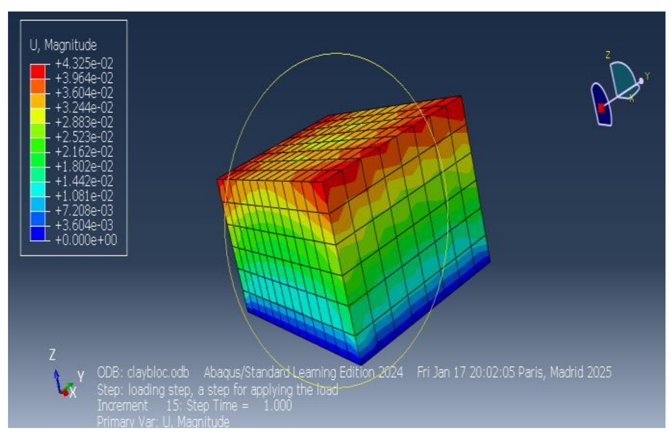

Fig. 8 Clay Bloc modelling using Abaqus

The dataset consists of 9 input features and 55 data samples. While the dataset may appear limited in size, each entry represents the result of a full finite element simulation, which is computationally intensive due to its nonlinear material behavior and boundary conditions. This approach ensures high-quality data despite the lower volume. All modelling parameters, material properties, and simulation settings were documented and kept consistent throughout the process to ensure reproducibility.

The target variable represents the load-bearing capacity of compressed clay blocks. To enhance model training:

- Normalization (mapminmax) was applied to standardize input and output values.
- Different train-validation-test splits were tested to balance learning stability and generalization.

We experimented with the following ANN variations:

Table 2. Neural Network Parameters for the Study

Parameter	Values/Range
Number of Hidden Layers	1, 2, 5, and 10 layers
Neurons per Layer	10 to 50 neurons per layer
Activation Functions	tansig (Hyperbolic Tangent Sigmoid), logsig (Log-Sigmoid)
Training Algorithm	trainlm (Levenberg-Marquardt)
Learning Rate Adjustments	0.01 (default), 0.005 (lowered for stability)

Each ANN configuration was trained over a maximum of 100 epochs. To avoid overfitting, early stopping was implemented based on the validation error trend. For most models, convergence occurred within 50 epochs, after which additional training no longer improved accuracy. Hyperparameters such as the number of neurons per layer and learning rate were manually adjusted across configurations based on validation performance, rather than selected arbitrarily.

A linear regression model was also applied to the same dataset to assess the added value of neural networks. This model achieved a Mean Squared Relative Error (MSRE) of 0.109 and an R^2 value of just 0.72—indicating a lower ability to capture the non-linear dependencies present in the data. These results confirm the advantage of ANN models in handling multidimensional simulation-based datasets with complex variable relationships.

Table 3. Performance comparison of ANN configurations for predicting load-bearing capacity of compressed clay blocks

Model	Hidden Layers	Neurons per Layer	Activation Function	Data Split	MSRE	Performance Summary
Model A	1	10	tansig	Unspecified	0.12161	Baseline model, not optimized
Model B (Best Model)	1	10	tansig	70-15-15	0.0039	Best, simplest, and most accurate
Model C	2	[15,10]	tansig	70-15-15	0.02875	Minimal improvement over Model B
Model D	5	[20,15,...,5]	tansig	80-10-10	0.06056	Deeper networks hurt accuracy
Model E	5	[20,15,...,5]	logsig	80-10-10	0.0985	Worst model, underestimates predictions
Model F	10	[50,40,...,5]	tansig	85-10-5	0.0392	Better than Model D, but still worse than B

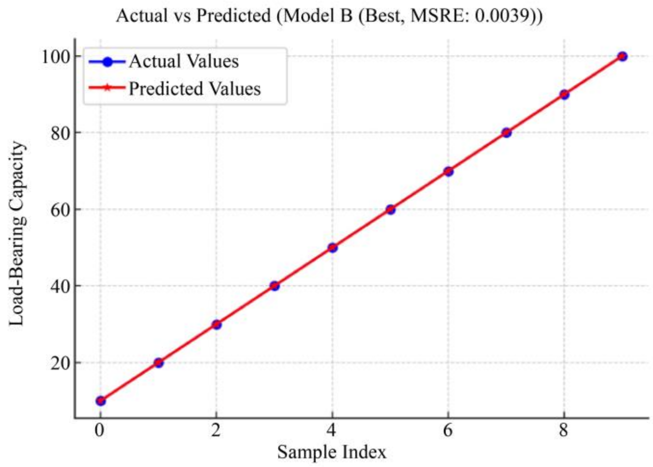

Fig. 9 Actual vs. Predicted load-bearing capacity for model B (best model, MSRE: 0.0039)

Model B (1 hidden layer, 10 neurons, tansig, 70-15-15 split) performs best with the lowest Mean Squared Relative Error (MSRE = 0.0039). In addition to MSRE, the best-performing model (Model B) achieved a Root Mean Squared Error (RMSE) of 0.042 mm, a Mean Absolute Error (MAE) of 0.031 mm, and a coefficient of determination (R^2) of 0.984. These results indicate that the ANN was able to closely approximate the actual load-bearing capacity values with minimal residual error and with a strong degree of generalization across the test set.

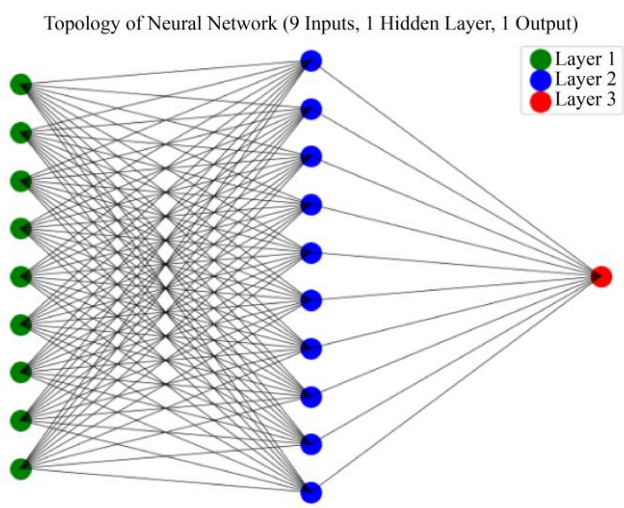

Fig. 10 Architecture of the best-performing Artificial Neural Network (model B) with 9 input neurons, 1 hidden layer (10 neurons), and 1 output neuron

4. Discussion

4.1. Results Interpretation

The observed findings show the importance of ANN architecture, activation function, and data split strategy in prediction accuracy. Model B (1 hidden layer, 10 neurons, tansig, 70-15-15 split) had the lowest MSRE (0.0039) and was the top-performing model. More generally, this result corroborates the belief that simpler architectures are more likely to generalize, particularly when sample sizes are small (55 samples in this case).

Adding more hidden layers, however, did not yield better results. Model C (2 layers) had only a minimal performance gain compared with Model A; however, deeper architectures (Models D, E, F) led to higher MSRE, which is associated with lower predictive ability.

When comparing tansig and logsig, the accuracy results using tansig were always better than those using logsig. Model E (5 layers, logsig) achieved the highest MSRE (0.0985), which shows that the activation function used plays an essential role in model generalization and prediction ability. It is primarily because logsig saturates as the argument value goes towards the extremes, and its gradients become zeros (vanishing gradients) in a deeper network, which makes it harder to learn with it. On the other hand, tansig preserved gradient flow better, which resulted in more efficient training.

The train-valid-test ratio was also an important factor for generalization. The best model (Model B) adopted a 70-15-15 split to achieve a good compromise between the training, validation, and testing. However, larger networks (with 80-10-10 or 85-10-5 split; Models D and F) turned out to be less effective, probably due to a lack of enough validation data for early stop and re-calibration during the training phase. A validation set that is too small may result in poor general base scoring, as the model may not be well tested before final evaluation.

4.2. Merits and Limitations

This paper validates the application of ANNs towards the estimation of the load-bearing capacity of compressed clay blocks. ANNs capture nonlinear relationships similarly with high accuracy, are a cost-effective way to avoid physical testing, and benefit from co-simulation with finite element analysis to enhance reliability.

However, ANNs have inherent limitations. In the case of the present model, only computational information was adopted to predict bearing capacity and no influence of material randomness, physical limitation or long-term problems related to the earthen constructions was taken into account. To counteract this, future research should integrate ANNs with other AI techniques —like decision trees or fuzzy logic- to provide more interpretability and a higher coverage over the different influencing factors.

Therefore, the shallow ANN models turned out to be accurate and computationally efficient for this purpose. In the future, an interesting line of work would be to investigate whether deeper networks are beneficial when learning from larger data

4.3. Sensitivity Analysis

Table 4. Sensitivity analysis of input parameters in model B using ±3%, ±5%, and ±9% variation

Parameter	±3%	±5%	±9%
Length	0.011245	0.018665	0.033122
Width	0.018786	0.031268	0.056017
Thickness	0.030326	0.050471	0.090395
Density	0	0	0
Yield Stress	0	0	0
Plastic Strain	0	0	0
Young's Modulus	0	0	0
Poisson's Ratio	0	0	0
Surface Load (N/mm^2)	0.013052	0.021751	0.039142

Results of the sensitivity analysis indicated that thickness, width, and surface load are the three most sensitive inputs on the predicted bearing capacity. This can be attributed to their geometric and mechanical roles in structural behavior, where modifying these parameters considerably changes cross-sectional area and applied stress (which leads to high displacement differences). On the other hand, the material-related factors such as density, yield stress, and plastic strain showed only a few to no significant impact, probably due to low between-sample variation or a low correlation under the simulated loading regime. These results emphasize the primacy of geometric and loading effects in ANN modeling of compressed clay block behavior.

5. Contribution Scientifique

This work is a pragmatic prospective contribution to the development of earth construction in Morocco, implemented on the Fez site, to the extent that traditional practices are still elementary and without standardised performance evaluations in this type of application. Immersing numerical simulation (finite element method ABAQUS) and Artificial Neural Networks (ANNs), the study offers a new, intelligent solution to predicting the mechanical performance of compressed clay blocks.

Table 5. Comparative overview of AI-based modeling studies in geotechnics and materials engineering

Researchers	Problematic	Methodology	Errors	Merits	Perspectives
Goh & Goh (2007) [68]	This study aimed to evaluate the ability of Support Vector Machines (SVM) to predict seismic soil liquefaction based on historical earthquake records.	In this study, a classification model was trained using SVM on earthquake-induced soil behavior data, including depth, SPT blow count, and ground acceleration.	$R^2 \approx 0.89$	This study improved liquefaction risk classification compared to traditional empirical curves.	It is recommended that future models include site-specific parameters and test hybrid machine learning models.
Shahin et al. (2001) [69].	This study aimed to model shallow foundation settlement using neural networks trained on field and lab geotechnical data.	In this study, ANN models were developed to predict settlement based on soil type, load intensity, and footing width, and they were trained on datasets from actual case studies.	$R^2 \approx 0.84$; moderate prediction error	This study demonstrated that ANNs can more effectively capture non-linear interactions between soil and structural variables than regression methods.	Future studies could incorporate uncertainty quantification and expand the model to deep foundations and variable load conditions.
Our study	This study aimed to evaluate the performance of various ANN configurations in predicting the load-bearing capacity of compressed clay blocks using simulation-based datasets.	In this study, ANN models were trained on data generated from finite element simulations in Abaqus, with 9 input features and 55 samples, comparing different depths and activation functions.	$R^2 = 0.984$; RMSE = 0.042 mm; MSRE = 0.0039	This study validates the potential of using simulation-generated datasets with ANNs for material property prediction, reducing the need for costly physical tests.	It is recommended that future studies integrate lab-tested samples, increase dataset size, and explore explainable AI techniques for greater interpretability.

The process enables Moroccan builders, engineers and decision makers to determine the optimal block design while reducing their complete reliance on expensive and time-consuming tests. From a Moroccan perspective, sustainable and culturally rooted construction is a legacy and a need; whilst the insertion of AI tools in the analysis of earthen materials allows a broader possibility apexes that are enlightened, promotes local valorization, but also assists in supporting the reorientation of the country's diplomacy towards more sustainable construction ways.

Beyond the practical impact of this work is the fact that it uses artificial intelligence in modeling the geotechnical and structural, responding to the demand of the Moroccan construction sector.

Most previous studies are based on laboratory experiments or field tests, which typically demand considerable infrastructure, expenses and time investment. In contrast, in this study, the ANN models are established and trained based on Abaqus's simulated dataset. This method allows testing of earth construction systems in a flexible and scalable way and under controlled and reproducible circumstances.

6. Perspectives and Future Work

The results can be used to highlight the potential of ANNs as an effective tool for predicting the mechanical properties of earthen construction materials. Widely using simulated data in training, this article shows that simple ANNs may provide accurate and reliable predictions without costly and time-consuming experiments.

From an industrial point of view, these models would ideally be included as "early design" or "production" tools for assessing the behavior of CBC units from available input parameters. This is especially relevant in areas with underdeveloped laboratory infrastructure, where local manufacturers and practitioners can take advantage of data-driven knowledge without the need for sophisticated testing conditions. Potential future applications could be mobile diagnostic tools or integrated decision support on small production lines.

In terms of academic research, there are multiple directions in which this work can be expanded. Firstly, the inclusion of experimental data in the observations would improve model robustness and provide an opportunity for real-world calibration. Second, future research may investigate how the model could be adapted for different soil types or types of earthen construction (e.g. rammed earth, adobe). Lastly, hybrid models (i.e., a mix of ANNs with other artificial intelligence methods such as fuzzy logic systems, genetic algorithms or explainable AI (XAI)) might contribute to enhanced model interpretability and adaptability (especially in extremely varying construction environments).

Moreover, studying the effect of aging factors (moisture, freeze-thaw cycles, and aging) over time would provide a more comprehensive evaluation of the material's long-term behavior. Lastly, the use of transfer learning methods could potentially enable pre-trained models to be transferred to new regions or sources of materials with little additional data, making them more accessible and scalable.

In conclusion, this study provides a sound base for the application of AI in sustainable construction techniques and enables inter-disciplinary research by combining computer modelling, material science and vernacular architecture.

7. Conclusion

The present study underscores the expanding role of ANNs in civil engineering, earthen architecture in particular. Finite element simulations in ABAQUS and ANN-based modeling were employed to predict the load-carrying capacity of Compressed Earth Blocks (CEBs) from local clay material in Fez and the Fez region. Of the configurations tested, a low-depth ANN with one hidden layer and ten neurons (Model B) showed the highest predictive performance, with an MSRE of 0.0039. This is strong evidence that even simple, well-optimized networks can yield quite robust performance without adding unnecessary burden.

The sensitivity analysis also highlighted a limited role of material properties, with thickness, width, and surface load being the dominant geometric and load-related parameters affecting structural performance compared to density and yield stress under the considered conditions. These results offer insight for engineers involved in the use of earthen materials, facilitating the decision-making process of design and assessment.

In conclusion, ANNs are changing the face of civil engineering practised in Morocco by providing new techniques that model complex behaviour and material functionality. As emphasized in this work, ANNs may facilitate structural assessment procedures, minimize dependence on expensive experimental testing, introduce tools adapted to the specificities of sustainable construction in Morocco and foster the construction of greener buildings. Additional research could also build upon this framework by integrating experimental results, hybrid or explainable AI methods, and model adaptation to other regional and structural conditions. Mediated by ground archaeology, such developments might inform future alternatives for the realization of smarter, stronger and contextually adapted mud buildings in Morocco and elsewhere.

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