Journal of Engineering Faculty, 1(2): 66-74, 2023

Journal of Engineering Faculty

| cumfad.cumhuriyet.edu.tr | Founded: 2023 Available online, ISSN Publisher: Sivas Cumhuriyet Üniversitesi

Prediction of Wear Properties of Experimental Produced Porcelain Ceramics Using Artificial Neural Networks (ANN)

Ahmet Gürkan Yüksek[1,a,*], Tahsin Boyraz[2,b], Ahmet Akkuş[3,c]

[1]Sivas Cumhuriyet Üniversitesi, Mühendislik Fakültesi, Bilgisayar Mühendisliği Bölümü
[2]Sivas Cumhuriyet Üniversitesi, Mühendislik Fakültesi, Metalürji Mühendisliği Bölümü
[3] Sivas Cumhuriyet Üniversitesi, Mühendislik Fakültesi, Makine Mühendisliği Bölümü
*Corresponding author

Research Article

History

Received: 13/12/2023
Accepted: 21/12/2023

Copyright

This work is licensed under Creative Commons Attribution 4.0 International License

ABSTRACT

In this study, the production and wear properties of porcelain ceramics produced by powder metallurgy method were examined and modelling with artificial neural networks was studied using the experimental data obtained. Porcelain ceramics were prepared by the powder metallurgy route. Mixtures prepared by mechanical alloying method in alumina ball mills were produced by sintering under normal atmospheric conditions after being shaped in a dry press. After drying, the powders were compressed by uniaxial pressing at 200 MPa. The green compacts were sintered at 1100-1200 °C for 1-5 h in air. Then, characterization studies of the sintered samples were carried out and the wear experimental results obtained were converted into data suitable for modelling with artificial neural networks. In the continuation of the study, experimental wear results using artificial neural networks were analysed and modelled. Wear load, wear time, sintering temperature and sintering time were used as artificial neural networks input variables. Wear values were taken as output variables of artificial neural networks. An artificial neural network was established for the prediction of wear properties of porcelain ceramic composites. As a result, the training results and test results were compared with the actual values to control the network performance. A good agreement was observed between the experimental and artificial neural networks model results. After the artificial neural networks estimation, confirmation tests were performed to confirm the experimental results.

Keywords: Ceramic; Porcelain; Wear; Artificial Neural Networks.

[a] agyuksek@cumhuriyet.edu.tr 0000-0001-7709-6360
[b] tahsinboyraz@cumhuriyet.edu.tr 0000-0003-4404-6388
[c] aakkus@cumhuriyet.edu.tr 0000-0002-6881-9333

How to Cite: Yüksek AG, Boyraz T, Akkuş A (2023) Prediction of Wear Properties of Experimental Produced Porcelain Ceramics Using Artificial Neural Networks (ANN), Journal of Engineering Faculty, 1(2): 66-74

Introduction

Porcelain is a hard, fine-grained, non-porous and usually translucent, vitrified and white ceramic consisting of kaolin, quartz and a feldspathic structure and fired at high temperatures [1-7]. Ceramic materials can significantly improve the response of components and parts for applications involving contact loadings due to their high hardness, potentially low friction, excellent corrosion resistance and ability to operate under extreme conditions such as high temperatures. The wear of ceramics is anisotropic and is associated with the crystalline structure as in metals [8-20].

Artificial neural networks emerged as a result of mathematical modelling of the learning process taking the human brain as an example. With artificial neural networks, the working of a simple biological nervous system is imitated. Networks formed by connecting neurons to each other have the capacity to learn, memorize and reveal the relationship between data. In artificial neural networks, the learning process is carried out using examples. During learning, entry and exit information is given and rules are set. Many different prediction models are tested in scientific studies. However, models that are simple, applicable, easy to implement and have the ability to predict accurately are preferred. In neural network based forecasting, an interpretable machine learning tool is important. On the other hand, prediction studies based on experimental data have been increasing rapidly recently [21-29].

Magnified ZnO on p-Si (100) substrate by pulsed filtered cathodic vacuum arc deposition system. Investigated the effects of incident angle on specular reflectance of ZnO thin film which was analysed and modelled using the experimental data and ANN model. To increase resistance to wear, Al7075 alloy is reinforced with Al_2O_3 ceramic particles. An artificial neural network was established to predict the tribological properties of the produced Al7075-Al_2O_3 composites. It was seen that there was a good agreement between experimental and ANN model results [30,31]. The model for predicting the mechanical properties of two-phase and three-phase composite ceramic tools such as Al_2O_3-(W, Ti)C and Al_2O_3-TiC-ZrO_2 was established by means of an artificial neural network. On the basis of the neural network toolbox in MATLAB, the neural network model for predicting the mechanical properties of the ceramic tool was trained to be reliable and the required programs were compiled. It was found from the research results that the established model based on the artificial neural network are available and effective in simulating the composition content and predicting the mechanical properties of the ceramic tool [32].

In this study, the production and wear properties of porcelain ceramics produced by powder metallurgy method were examined and modelling with artificial neural networks was studied using the experimental data obtained. Artificial neural network method is used to anticipate the tribological conduct of porcelain ceramic utilizing neural network tool compartment of MATLab and then the test and artificial neural network results were compared.

Materials and Methods

Setting up experimental setups and taking physical measurements in experimental studies may involve some difficulties for many researchers. Experimental results may not be collected on the sample as much as desired due to uncontrollable reasons, financial inadequacies, impossibilities or other reasons. In these cases, this gap is tried to be filled with simulation data. At this point, machine learning algorithms fill an important gap in predicting the results of untested data with patterns learned from data taken from experiments at certain intervals. This proposed study generates simulation results for new data with very high success by defining the effective aspects of the two basic machine learning theories of the artificial neural network approach, the patterns of an experimental study.

The most important problems of experimental models are experiment costs, setup times, material-device management problems, etc. factors that affect the process of the experiment, such as If the accuracy of the systems that can be simulated with statistical or mathematical models can be improved to support the model, these operations can be performed in the simulation environment. Especially since artificial neural network algorithms are trained on the data or the history of the model, they better models the patterns of the systems.

Materials production

In this study, the production and wear properties of porcelain ceramics produced by powder metallurgy method were examined and modelling with artificial neural networks were studied using the experimental data obtained. Porcelain ceramics were prepared by the powder metallurgy route. Mixtures prepared by mechanical alloying method in alumina ball mills were produced by sintering under normal atmospheric conditions after being shaped in a dry press. The mixture powders were compacted to preforms of 56x12x10 mm by uniaxial pressing at 200 MPa. The green compacts were sintered at 1100-1200 °C for 1-5 h under air using a heating rate of 5 °C min^{-1} in a high temperature furnace (Protherm™ Furnace). Plint brand abrasion tester was used for the abrasion tests of ceramics. Steel disc is used as wear disc. Wear tests were performed on each sample at 5, 10, 15 and 20-minute wear duration and 70, 90, 120 N force. First, the specimen was measured with a precision scale of 0.0001 g, and the amount of wear was determined by measuring again after the specified wear time (Figure 1). Then, characterization studies of the sintered samples were carried out and the wear experimental results obtained were converted into data suitable for modelling with artificial neural networks.

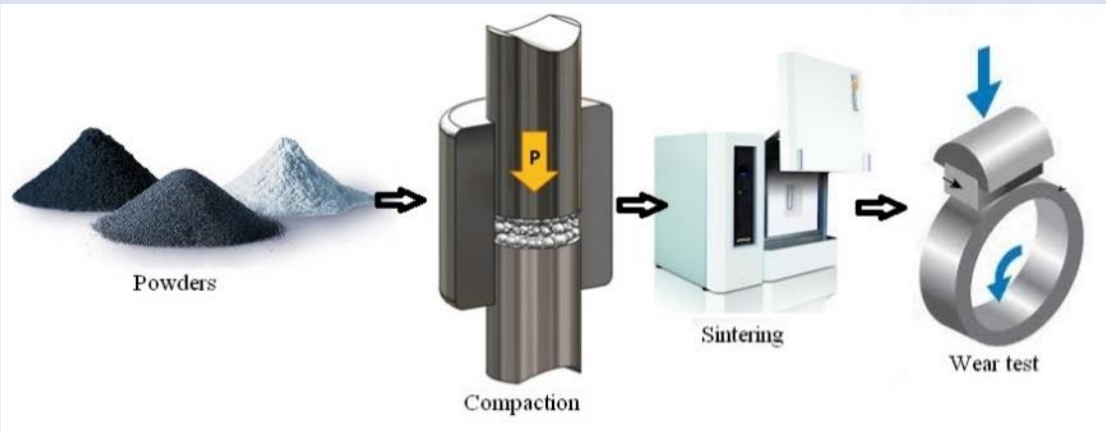

Figure 1. Ceramic production stages

Machine learning based approach of System Modelling

Artificial Neural Networks is a field of artificial intelligence based on information processing systems learning and producing results by detecting hidden patterns in data rather than using algorithms [33,34]. Systems based on ANN are based on the logic of modelling problem-solving abilities through human experience, intelligence and reasoning. They stand out especially with their ability to solve complex and nonlinear problems. It has distinct advantages in solving real-world problems, preferably non-linear, in many different disciplines. For this reason, it has become an increasingly preferred approach in recent years. Complex calculations, especially those performed on dense data sets, can produce results faster with the effect of learning-based developments in hardware and software theories. Computers with ANN learning capabilities; They are equipped with the ability to make decisions by perceiving the pattern in a data set using mathematical and statistical techniques, which is called learning. These qualities focus on the idea that computers can detect patterns in data and make decisions with less external support and constitute an important sub-branch of artificial intelligence. Instead of codes defining the computer's operations, it defines an algorithm process that is adapted to instantiate the code's intended behaviour. The resulting program consisting of the algorithm and associated learned parameters is considered the trained model. A basic ML learning flow diagram is shown in Fig. 2.

Data scientists have focused on a wide variety of machine learning algorithms based on prediction, classification, and clustering. They try to show that the systems they developed are easier to implement and perform better in many studies than classical statistical approaches. Thus, interest in theories described as innovative and smart is increasing. Unlike classical statistical approaches, ANN uses an algorithm to learn the relationship between the response and its predictors and does not focus on assumptions such as which model to assume, how the response is distributed, and whether the observations are independent. In contrast, the machine learning approach recognizes that the process that generates data is complex and unknown, tries to learn the response by observing inputs and responses, and deals with determining system parameters to find dominant patterns [35,36].

Particularly in some engineering fields, the difficulties and high costs of setting up experimental setups for different parameters or environmental structures during processes based on experimental studies are known. Challenges such as equipment and material requirements, measurement accuracy, data inconsistency, experiment continuity, parameter adjustment, data analysis complexity, cost and time management reflect the complexity of experimental studies. However, all these mentioned challenges can be solved with good planning, proper resource management and expertise. The ability of machine learning methods to produce and discover new knowledge by learning from data offers an innovative and intuitive approach to experimental studies in overcoming all these difficulties. These approaches, which aim to model parametric values that cannot be realized experimentally with machine learning algorithms, based on the results of experiments carried out with certain parameters under existing or favourable conditions, are accepted in many different disciplines.

A large majority of the studies that produce effective results using ANN theory are on determining the relationship between the dependent variable and one or more independent variables. ANN models are trained with different parameters, and an ANN structure that is capable of best predicting the behaviour of the independent variable at different dependent variable values is tried to be established. The aim of this proposed study is to model the wear behaviour of aluminium titanate and mullite added porcelain ceramics produced by the powder metallurgy method with the ANN approach, to determine the most successful model and to examine the differences on these models. It is to propose a model that will successfully represent the problem at values that cannot be realized experimentally, by using a wide range of experimentally produced data sets with different input parameters.

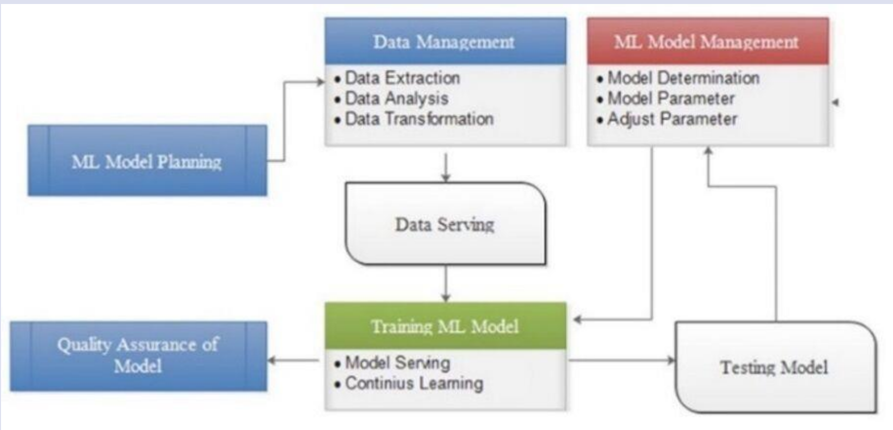

Figure 2. Machine learning flow diagram.

Artificial Neural Networks (ANN)

The mathematical model of the neural network system of the human brain has constantly attracted the attention of researchers, and as a result of intensive studies, the approach called ANN was developed. ANN is an approach that offers solutions to numerous problems in different disciplines, which have been on the agenda especially in the last quarter century. The most succinct definition of ANN was given by Haykin as a massively parallel combination of simple processing units that can acquire information from the environment through a learning process and store the information in their connections [23]. It is accepted as the representation of the human ability to perform mental activities such as reasoning, making sense, generalizing and learning by a machine capable of processing information. An attempt has been made to model the computational mechanism of the most basic processing element (neuron) that forms the mentioned model and the behaviour of the neuro-physical basic processing element (neuron) of the human brain, which is still not fully understood. In an academic publication they prepared in 1943, McCulloch and Pitt described the properties of the basic neuron type by modelling its behaviour for binary input [37]. In a basic ANN cell, there is an input layer, weight layer, summation function layer, activation function layer and output layer, as seen in Fig. 3.

The data obtained from the inputs is transmitted to the neuron through weight values and determines the value of the input with the effect of the weights. The net value in the neuron is the sum of each input and the product of the weights of this input. This value applied to the activation function determines the neuron output. The activation function is generally determined as a differentiable nonlinear function [38].

ANN is a system approach that aims to model the parallel and distributed structure of brain cells connected to each other, and is created by artificial nerve cells imitating this model. Its architecture is organized as different layers and the interconnection of processing cells in these different layers (Fig. 4) and can be developed with hardware circuits or software. Similar to the information processing ability of the brain, ANN includes learning algorithms that manage the updating of ANN weights to collect data following a learning phase following the training process, store this data with the weight values formed between cells, and generalize to produce the most appropriate output for the problem being studied [39]. The concept of learning from data, which is the determining power of ANN, includes learning algorithms based on updating the weights connecting neurons in other layers in order to produce the targeted result data.

Backpropagation algorithm is the most preferred algorithm for training feedforward ANNs [40]. It calculates the gradient of the loss function based on the network weights and is more efficient than directly calculating the gradient based on each individual weight. This feature allows the use of gradient methods to rearrange weights at the stage of training multilayer networks and minimizing the loss on them; Variants such as gradient descent or stochastic gradient descent are often used. The purpose of the backpropagation algorithm is to calculate the partial derivatives of the cost function C (Equation 1) as ∂C/∂w and ∂C/∂b with respect to any bias w or b in the network.

$$C = \frac{1}{2n} \sum_x \|y(x) - a^L(x)\|^2 \tag{1}$$

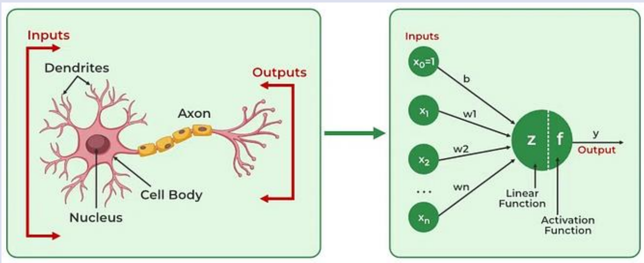

Figure 3. Explaining the Structure of a Neuron and a basic ANN cell.

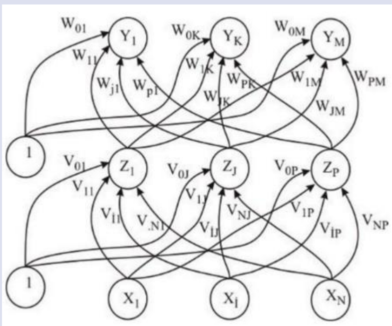

Figure 4. Multilayer feedforward ANN model.

Design of The Model and Experimental Results

Data Set Preparation and Experimental System and Data Collection

In this study, using ANN, wear results depending on test time and load were performed on Porcelain data sets, and the results of the experiments that were not available for similar studies were modelled. All the data in this study were collected from this article (T. Boyraz and A. Akkuş, Investigation of wear properties of mullite and aluminium titanate added porcelain ceramics, Journal of Ceramic Processing Research, 2021, 22(2), 226-231) [1]. A total of 108 sets of data points (including sintering time and temperature, load and force applied for the wear test and the amount of wear) were systematically extracted from the experimental information. Some mismatches in the extracted raw data that make them unsuitable for direct use in machine learning algorithms are conditioned by pre-processing.

Establishing and Application of the Model

The most significant factor on the success of ANN models is that the data set used for training best reflects the problem pattern being studied [21]. Model development processes with ANN are shown in Figure 2. From the perspective of system analysis, the initial part of this flow is the step where the problem is defined, its boundaries are defined, flow maps are determined and the process as control is created, and it is decisive on the flows of the entire model. The data set preparation in the second part is the creation of a data set that can respond to the output results produced by the developed model or system and represent the problem in the best way. In the next steps, using this data set, the model is trained with the parameters that will be given the most optimum value. Determination of parameters is accepted according to the output produced by the model being studied. In the last step, the outputs produced by the established ANN model are compared with the real measurement values by data mining and the success of the model is tested [22]. The parameters constituting the data set used for the training of the ANN model in this study are given in Table 1.

It is necessary to choose the parameters of the model to best represent the pattern structure of the data set on which the models are trained and to reflect the effects of the input data on the model. For this reason, continuous training was carried out by making changes to the parameters for the model that would produce the best output results. To test the outputs of the trained model, the one with the best representation power among the values produced by statistical value measurement units (Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and R Squared (R^2) [23]. Regression (R2) coefficient is a statistical measure of the relationship between two variables. RMSE is used in areas such as machine learning and determines the performance of a model by measuring the differences between actual values and predicted values. MAPE is used to evaluate the performance of a prediction model and measures how close it is to the true values, specifically taking into account the percentage error rates of the predictions. MAE is used to evaluate the performance of a forecasting model and refers to the average of the absolute differences between the predictions and the true values. The parameter combination was determined (Table 2).

Before the ANN model started to be trained, the values containing the 15-minute time measurements of the entire data set were initially separated from the data set to be used for training as the "Test Data Set" in order to check the consistency of the model structure developed later. Measurements of 5, 10 and 20-minute time are reserved as "Model Training Set" for the development of the models to be proposed. After the ANN architecture and parameters are determined with the Model Training Set, the success of this model is determined by the outputs produced by presenting the Test Data Set to the model. The important point is that the Test Data Set was not presented to the model during training of the model, it was used to test the success of the model by checking the performance values after the training of the model. The statistical value measurements given in Table 2 reflect the results of checking the models produced with the "Training Data Set" with the "Test Data Set".

Table 1. ANN Model Dataset Parameters.

Parameter Name	Unit	Parameter Structure
Wear Force	Newton	$X_1 \rightarrow$ Input
Wear Time	Minute	$X_2 \rightarrow$ Input
Fired Temperature	°C	$X_3 \rightarrow$ Input
Fired Time	Hour	$X_4 \rightarrow$ Input
Wear Volume	mm^3	$Y_1 \rightarrow$ Output

Table 2. Test data set, Training Data Sets and Statistical value measures for Porcelain.

Model TestData Set		Training Data Set			
		All	**Train**	**Test**	**Validation**
MAPE	0,3017	0,1150	0,0888	0,2485	0,1060
MAE	2,7719	1,2995	0,9549	2,6017	1,6340
RMSE	3,3311	2,0610	1,3680	3,6624	2,5241
R^2	0,7500	0,9347	0,9720	0,8120	0,9249

Fig. 5 shows the Scatter Plot Between Input and Output Data. The "model training set all data" graphs of ANN model results produced for 15-minute time with the model training set are shown in Fig. 6. (a) R^2 graphs, b) Comparison graphs of Actual Value and Outputs Produced by the Model and c) Actual Value and Output Differences (Error) Graph Produced by the Model).

As can be seen from the figures and Table 2, very successful results were obtained in the study conducted with ANN.

In this study, the factors affecting the wear behaviour of porcelain ceramics were analysed quantitatively using ANN. According to the machine learning analysis performed in this study, the applied load (X_1) and application time (X_2) in the wear test, and the sintering temperature (X_3) and time (X_4) are the most critical parameters in estimating the amount of wear(Y). While creating the ANN, the training data set was divided into 4 parts (Training, Testing, Validation and All data set).

Based on the approach of comparing the success of the model with the Test data set and the result produced, a R^2 value of 0,7500 for 15 minute. R^2 value was found to be 0.938 in all data set calculations. The R^2, MAPE and RMSE values obtained for the ANN model are 0.7500, 0.3017 and 3,3311, respectively, for 15 minute and are within the quite acceptable range. Model success is also observed from the calculation values of other statistical indicators. As can be seen from the graphs in the tables, the distribution of R^2 values and the unity representation of the actual calculated values support the final success of the model.

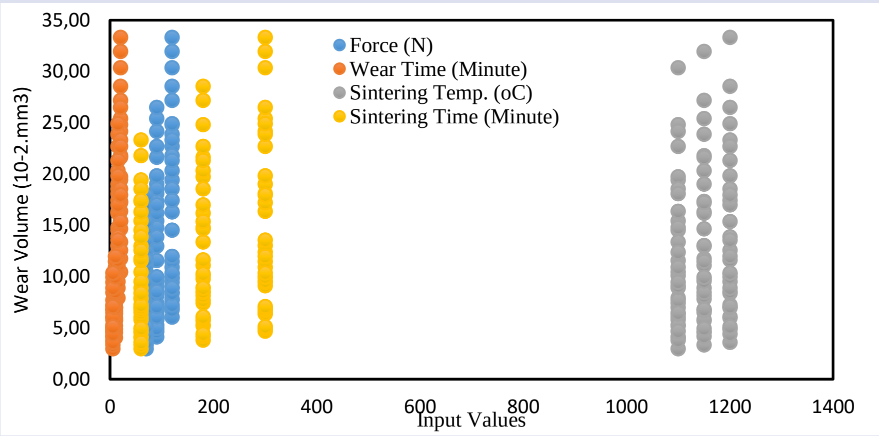

Figure 5. Scatter Plot Between Input and Output Data

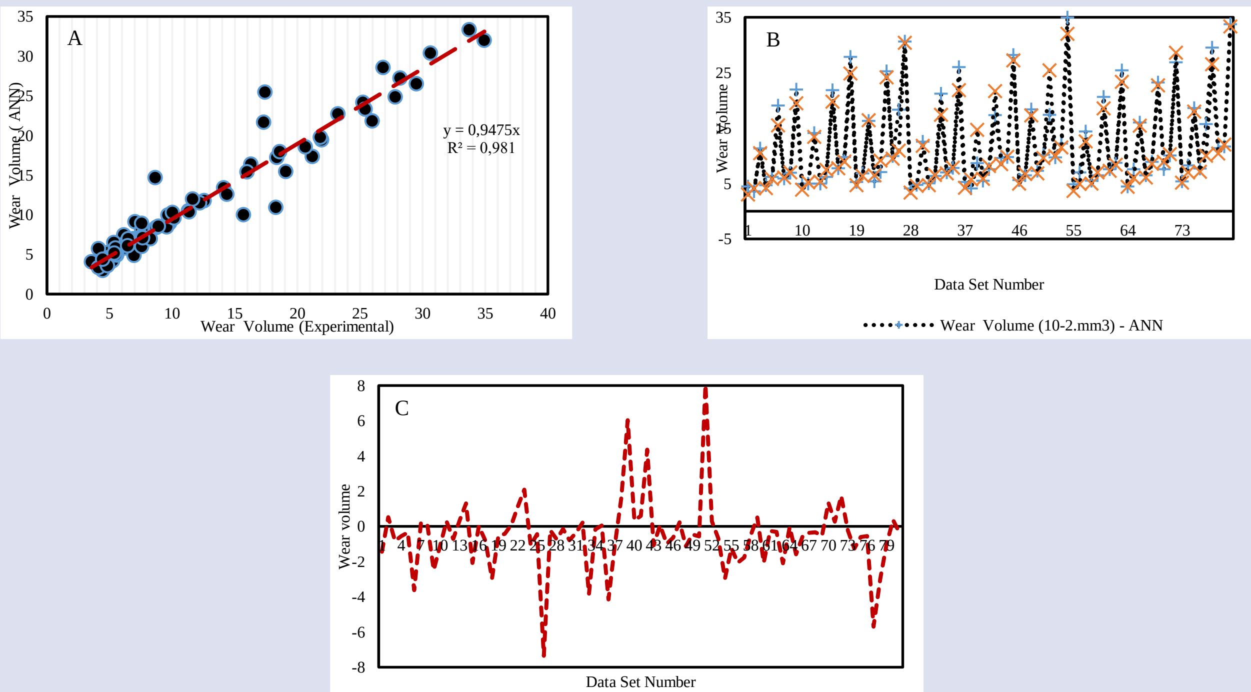

Figure 6. Model Training Set All Data graphs of ANN model results produced for 15-minute time with the model training set; a) R^2 graphs, b) Comparison graphs of Actual Value and Outputs Produced by the Model and c) Actual Value and Output Differences (Error) Graph Produced by the Model.

Conclusions

Setting up experimental setups and taking physical measurements in experimental studies also bring some problems for researchers. Not being able to perform experiments on the desired number of samples due to some uncontrollable reasons or inadequacies is one of them. In these cases, this gap is tried to be filled with simulation data. At this point, machine learning algorithms fill an important gap in predicting the results of untested data with patterns learned from data taken from experiments at certain intervals. The proposed study produces simulation results for new data with very high success by defining the effective aspects of the basic machine learning theories of the ANN approach, the patterns of an experimental study.

In this study, a highly sensitive machine learning (ML) algorithm based on ANN is introduced to predict the wear properties of porcelain ceramics. Factors affecting wear were quantitatively analysed using ANN. According to the machine learning analysis performed in this study, the applied load (X_1) and application time (X_2) in the wear test, and the sintering temperature (X_3) and time (X_4) are the most critical parameters in estimating the amount of wear(Y). The predictive model presented in this study not only provides a set of process parameters to obtain the desired the wear amount of the produced porcelain ceramics in a practical scenario, it will also shed light on other ceramic material studies.

The results of this study are;

- Porcelain ceramics were produced by powder metallurgy method and their wear properties were tested experimentally. Steel discs were used as wear disc. Wear tests were performed time (0-20 min.) and force (70-120 N) on each sample. As a result of wear tests, the amount of wear increased as the load and time increased.
- The R Squared (R^2) values of the outputs produced by the ANN model were sorted using the Test Data Set, Validation Data Set, All Data Set and Training Data Set order and the most appropriate model was selected. According to these results, when the graphic and produced numerical values of the R^2 value, which is the basic indicator, are examined, it is seen that the model succeeds in representing the real system.
- A R^2 value of 0.7500 for 15 minute was achieved based on the approach of comparing the success of the model with the Test data set and the result produced. R^2 value was found to be 0.938 in all data set calculations.
- The R^2, MAPE and RMSE value obtained for the ANN model are 0.7500, 0.3017 and 3,3311 respectively for 15 minute, which are in the well acceptable range and hence the developed model can be adapted effectively.

Model success is also observed from the computational values of other statistical indicators. As can be seen from the graphics in the tables, the distributions of the R^2 values and the association representation of the actual-calculated values support the final success of the model.

Setting up experimental set-up, managing processes and conducting experiments for varying ranges of parameters in experimental studies can be fraught with difficulties. Factors such as material and equipment requirements, measurement precision, data inconsistencies, experimental continuity, parameter optimisation, data complexity, cost and time management all contribute to the complexity of experimental work. However, these challenges can be overcome with careful planning, resource management and expertise. Machine learning methods bring an innovative and intuitive understanding to these challenges in experiments, offering the ability to learn from data and generate meaningful knowledge. The results of experiments conducted under certain conditions have been accepted in many different disciplines with the expectation that parametric values that cannot be obtained experimentally can be modelled thanks to the data processing capabilities of machine learning algorithms. These approaches are enlightening for similar studies.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] T. Boyraz and A. Akkuş, Investigation of wear properties of mullite and aluminium titanate added porcelain ceramics, Journal of Ceramic Processing Research, 2021, 22(2), 226-231.

[2] Ahmet Akkuş and Tahsin Boyraz, 'Fabrication and characterization of aluminium titanate and mullite added Porcelain ceramics', J. Ceram. Proc. Res., 20[1] (2019) 54~58.

[3] O. Turkmen, A. Kucuk, S. Akpinar, ''Effect of wollastonite addition on sintering of hard porcelain'', Ceram. Inter. 41[4] (2015) 5505–5512.

[4] M.Saclı, U. Onen, T. Boyraz, ''Microstructural Characterization and Thermal Properties of Aluminium Titanate / Porcelain Ceramic Matrix Composites'', *Acta* Physica *Polonica* A, 127[4] (2015) 1133-1135.

[5] S. Kitouni, A. Harabi, '' Sintering and mechanical properties of porcelains prepared from algerian raw materials'', Cerâmica, 57 (2011) 453-460.

[6] S.Y.R. Lopez, J.S. Rodriguez, S.S. Sueyoshi, ''Determination of the activation energy for densification of porcelain stoneware'', J. Ceram. Process. Res. 12 [3] (2011) 228–232.

[7] J. Martin-Marquez, J.M.a. Rincon, M. Romero, ''Effect of firing temperature on sintering of porcelain stoneware tiles'', Ceram. Int., 34 (2008) 1867–1873.

[8] J. Martin-Marquez, A.G. De la Torre, M.A.G. Aranda, J.M.a. Rincon, M. Romero, ''Evolution with temperature of crystalline and amorphous phases in porcelain stoneware'', J. Am. Ceram. Soc. 92 (2009) 229–234.

[9] Y. Iqbal, E.J. Lee, ''Microstructural evolution in triaxial porcelain'', J. Am. Ceram. Soc. 83 (2000) 3121–3127.

[10] Ahmet Akkuş and Tahsin Boyraz, ''Investigation of wear properties of CaO, MgO added stabilized zirconia ceramics produced by different pressing methods'', J. Ceram. Proc. Res., 19[3] (2018) 249~252.

[11] D. H.Buckley, K.Miyoshi, ''Friction and wear of ceramics'' , Wear, 100[1–3](1984)333-353.

[12] Y. Kong, Z. Yang, G. Zhang, Q. Yuan, ''Friction and wear characteristics of mullite, ZTM and TZP ceramics'', Wear 218 (1998)159-166.

[13] C. Baudín, AA. Tricoteaux, H. Joire, ''Improved resistance of alumina to mild wear by aluminium titanate additions'', J. Eur. Ceram. Soc., 34 (2014) 69–80.

[14] H.Y. Yu, Z.B. Cai, P.D. Ren, M.H. Zhu, Z.R. Zhou, ''Friction and wear behavior of dental feldspathic porcelain'', Wear, 261 (2006) 611–621.

[15] S. Bueno, L. Micele, C. Melandri, C. Baudin, G. De Portu, ''Improved wear behaviour of alumina–aluminium titanate laminates with low residual stresses and large grained interfaces'', J. Eur. Ceram. Soc., 31 (2011) 475–483.

[16] S. Taktak, M.S. Baspinar, ''Wear and friction behaviour of alumina/mullite composite by sol–gel infiltration technique'', Materials and Design, 26 (2005) 459–464.

[17] H.H. Luo, F.C. Zhang, S.G. Roberts, ''Wear resistance of reaction sintered alumina/mullite composites'', Materials Science and Engineering A, 478 (2008) 270–275.

[18] Öztürk, Ç., Akpınar, S. & Tığ, M. Effect of calcined colemanite addition on properties of porcelain tile. J Aust Ceram Soc 58, 321–331 (2022).

[19] Serragdj, I., Harabi, A., Kasrani, S. et al. Effect of ZrO2 additions on densification and mechanical properties of modified resistant porcelains using economic raw materials. J Aust Ceram Soc 55, 489–499 (2019).

[20] Aydin, T., Bican, O. & Gümrük, R. Investigation of wear resistance of the porcelain tile bodies by solid particle impingement using alumina particles. J Aust Ceram Soc 56, 525–531 (2020).

[21] M. Madhiarasan and M. Louzazni, Analysis of Artificial Neural Network: Architecture, Types, and Forecasting Applications, Journal of Electrical and Computer Engineering, 2022, V.2022, ID 5416722.

[22] Shekhawat, P. Agarwal, A. Singh, A. Patnaik, Prediction of thermal and thermo-mechanical behavior of nano-zirconia reinforced aluminium matrix composites, Materialwissenschaft und Werkstofftechnik (Materials Science and Engineering Technology), 53 (2022) 1216–1228.

[23] Haykin, S. (1994) Neural Networks: A Comprehensive Foundation. Macmillan Publishing, New York.

[24] M. Hassan, A. Alrashdan, M. T. Hayajneh, A. T. Mayyas, Prediction of density, porosity and hardness in aluminium–copper-based composite materials using ANN, Journal of Materials Processing Technology, 209/2 (2009) 894–899.

[25] L. V. Fausett, Fundamentals of neural networks: architectures, algorithms and applications, Englewood Cliffs, NJ: Prentice-Hall, 1994.

[26] J. D. Kelleher, B. Mac Namee, ve A. D'Arcy, Fundamentals of machine learning for predictive data analytics: algorithms, worked examples, and case studies. Cambridge, Massachusetts: The MIT Press, 2015.

[27] E. Guresen ve G. Kayakutlu, Definition of artificial neural networks with comparison to other networks, Procedia Comput. Sci., 3 (2011) 426-433.

[28] L. Breiman, Statistical Modeling: The Two Cultures (with comments and a rejoinder by the author), Stat. Sci., 16/3 (2001).

[29] A. Ramanathan, L. L. Pullum, F. Hussain, D. Chakrabarty, ve S. Kumar Jha, "Integrating Symbolic and Statistical Methods for Testing Intelligent Systems Applications to Machine Learning and Computer Vision", içinde Proceedings of the 2016 Design, Automation & Test in Europe Conference & Exhibition (DATE), Research Publishing Services, (2016) 786-791.

[30] A. G. Yuksek, E. T., Senadim S. Elagoz, Modeling of reflectance properties of ZnO film using artificial neural networks, Journal of optoelectronics and advanced materials, 17/11-12(2015) 1615-1628.

[31] R. Pramod, G. B. V. Kumar, P. S. S. Gouda, A.T. Mathew, A Study on the Al2O3 reinforced Al7075 Metal Matrix Composites Wear behavior using Artificial Neural Networks, Materials Today: Proceedings. 5 (2018) 11376–11385.

[32] C.Z. Huang, L. Zhang, L. He, J. Sun, B. Fang, B.Zou, Z.Q.Li, X. Ai, A study on the prediction of the mechanical properties of a ceramic tool based on an artificial neural network, Journal of Materials Processing Technology, 2002, V.129/1–3(2002) 399-402.

[33] M. Kubat, Neural networks: a comprehensive foundation by Simon Haykin, Macmillan, 1994, ISBN 0-02-352781-7., Knowl. Eng. Rev., 13 (1999) 409-412.

[34] F. B. Fitch, Warren S. McCulloch and Walter Pitts. A logical calculus of the ideas immanent in nervous activity. Bulletin of mathematical biophysics, 5 (1943)115–133.", J. Symb. Log., 9/ 2, 49-50, 1944.

[35] L. V. Fausett, Fundamentals of neural networks: architectures, algorithms, and applications. Englewood Cliffs, NJ: Prentice-Hall, 1994.

[36] K. Gurney, An Introduction to Neural Networks, CRC Press, 2018.

[37] D. E. Rumelhart, G. E. Hinton, ve R. J. Williams, Learning representations by back-propagating errors, Nature, 323/6088, 533-536, 1986.

[38] D. Graupe, Principles of Artificial Neural Networks, 2. bs, c. 6. içinde Advanced Series in Circuits and Systems, vol. 6. WORLD SCIENTIFIC, 2007.

[39] X. Hu, DB-HReduction: A data preprocessing algorithm for data mining applications, Appl. Math. Lett., c. 16, sy 6, ss. 889-895, Ağu. 2003,

[40] J. M. González-Sopeña, V. Pakrashi, ve B. Ghosh, An overview of performance evaluation metrics for short-term statistical wind power forecasting, Renew. Sustain. Energy Rev., 138, 110515, 2021,