Academic Research Journal of Technical Vocational Schools

| artes@cumhuriyet.edu.tr | Founded: 2023 Available online, ISSN: 2822-5880 Publisher: Sivas Cumhuriyet Üniversitesi

Regression Modelling to Study Wear Properties of Experimental Produced Porcelain Ceramics

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ResearchArticle

History

Received: 19/12/2023
Accepted: 04/01/2024

ABSTRACT

In this study, the production and wear properties of porcelain ceramics produced by powder metallurgy method were examined and modelling with regression 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. 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 regression. In the continuation of the study, experimental wear results using regression was analysed and modelled. Wear load, wear time, sintering temperature and sintering time were used as regression input variables. Wear values were taken as output variables of regression. A regression 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 regression model results. After the regression estimation, confirmation tests were performed to confirm the experimental results.

Keywords: Ceramic, Porcelain, Wear, Regression.

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How to Cite: Yüksek GA, Boyraz T, Akkuş A, (2023). Regression Modelling to Study Wear Properties of Experimental Produced Porcelain Ceramics, Academic Research Journal of Technical Vocational Schools, 2(2):25-31

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 (Boyraz and Akkuş, 2021; Akkuş and Boyraz, 2019; Turkmen, et al., 2015; Saclı, et al., 2015; Kitouni and Harabi, 2011; Lopez, et al., 2011; Martin-Marquez, et al., 2009). 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 (Martin-Marquez, et al., 2009; Iqbal and Lee, 2000; Akkuş and Boyraz, 2018; Buckley and Miyoshi, 1984; Kong, et al., 1998; Baudín, et al., 2014; Yu, et al., 2006; Bueno, et al., 2011; Taktak, 2005; Luo, et al., 2008; Öztürk, et al., 2022; Serragdj, et al., 2019; Aydin, et al., 2020). 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 (Madhiarasan and Louzazni, 2022; Shekhawat, et al., 2022; Haykin, 1994; Fausett, 1994; Kelleher, et al., 2015; Guresen and Kayakutlu, 2011; Breiman, 2001; Ramanathan and Pullum, et al., 2016). Regression analysis is a predictive modelling technique that investigates the relationship between the dependent target and the independent variable. This technique is used for forecasting, time series modelling and finding the causal effect relationship between variables.

Modelling and prediction studies have been carried out using the regression method in many areas. Regression helps market researchers, data analysts, data scientists uncover and evaluate the best set of variables to use to create predictive models (Sykes, 1993). Use of multivariate regression model to measure the impact of asset prices (Yüzük, 2019; Binder, 1985). Turkey's electrical energy consumption forecast until 2050 using the linear regression technique (Yumurtacı and Asmaz, 2004), examining the impact of crude and processed oil prices on macroeconomic quantities in the Turkish oil market (Abdullah, 2005), Estimating the lignite coal consumer surplus in Turkey with a regression model in which the annual lignite coal demand amount depends on the real lignite coal price, the real price of the substitute product natural gas, real Gross National Product and time variables (Demirbuğan, 2006) and Monte Carlo simulation application of structural change testing in multivariate regression model through energy demand models (Bernard, et al., 2007) regression method was used in their studies. Multiple regression analysis model was used to find effective energetic solutions for monthly heating demand prediction for the residential sector (Catalina, et al., 2008). Turkey's primary energy resources are oil, natural gas and Statistical analysis was performed for coal, the variables used in the multiple regression analysis were determined, and linear, logarithmic and square models were established to reach statistically and economically significant models for all three energy sources (Catalina, et al., 2008). Residential electricity and fuel in multivariate regression model consumption simulations were used (Al-Ghandoor, et al., 2009). In the Turkish energy market, factors affecting energy efficiency and consumption demand were analysed with a regression model (Özkan, 2016; Karaca and Karacan, 2016).

Modeling of reflectance properties of ZnO film using artificial neural networks, A Study on the Al2O3 reinforced Al7075 Metal Matrix Composites Wear behavior using Artificial Neural Networks and a study on the prediction of the mechanical properties of a ceramic tool based on an artificial neural network for it are some of the studies carried out in the field of materials science (Yuksek, et al., 2015; Pramod, et al., 2018; Huang, et al., 2002).

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

Material 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 regression 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. The mixture powders were compacted to preforms of 56x12x10 mm by uniaxial pressing at 200 MPa. The green compacts were sintered at 1100-1200 ºC for 1-5 h under air using a heating rate of 5 ºC 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 regression.

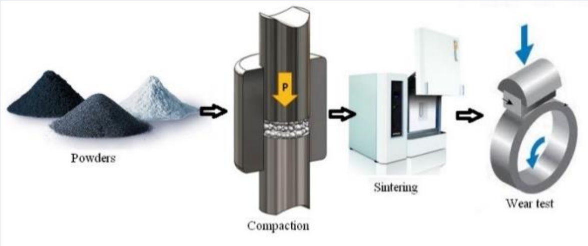

Figure 1. Ceramic production stages

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 (Kubat, 1994; McCulloch, et al., 1943). 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 Figure 2. shows the general workflow for both classification and regression type of machine learning approaches.

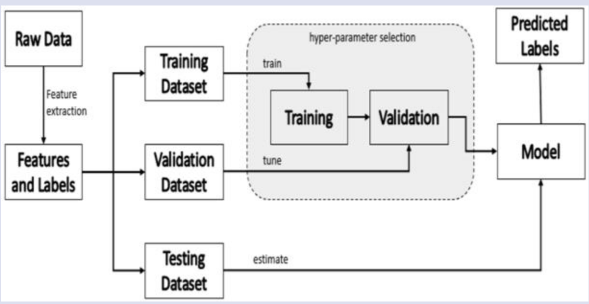

Figure 2. General workflow diagram of machine learning algorithms

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 (Fausett, 1994; Basavaraju, et al., 2019).

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.

Regression

Regression analysis using artificial neural networks (ANNs) is a statistical technique used to predict the value of a dependent variable based on one or more independent variables. ANNs are trained on a dataset that includes input and output values for a set of observations and can handle non-linear relationships and large amounts of data. However, they can be more difficult to interpret than other regression models and may require more data and computational resources to train. Multiple linear Regression analysis using artificial neural networks (ANNs) is a machine learning technique that utilizes neural networks to predict a continuous output variable based on input variables. It is a powerful tool for modelling complex, non-linear relationships and can be applied to a wide range of fields such as finance, economics, engineering, and more. There are two main types of ANNs for regression analysis: feedforward and recurrent neural networks. Feedforward neural networks are the most commonly used type and are composed of layers of neurons that process the input data and produce the output. In contrast, recurrent neural networks are designed to process sequential data and have loops that allow information to flow through the network multiple times. Both types of ANNs have their strengths and can be used depending on the problem and dataset.

Showing meaningful relationships between the dependent variable and the independent variable, show the strength of the effect of more than one independent variable on a dependent variable and it also enables comparison of the effects of variables measured at different scales are some of the advantages of regression analysis. These benefits help market researchers, data analysts, data scientists uncover and evaluate the best set of variables to use to create predictive models. The method for regression can be determined by looking at the number of independent variables, the type of dependent variables and the shape of the regression line (Yüzük, 2019).

Design of The Model and Experimental Results

Data Set Preparation and Experimental System and Data Collection

In this study, using regression, 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 (Boyraz and Akkuş, Investigation of wear properties of mullite and aluminium titanate added porcelain ceramics, Journal of Ceramic Processing Research, 2021, 22(2), 226-231). 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 regression models is that the data set used for training best reflects the problem pattern being studied. Model development processes with regression 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 regression model are compared with the real measurement values by data mining and the success of the model is tested. The parameters constituting the data set used for the training of the regression model in this study are given in Table 1.

Table 1. Regression Model Dataset Parameters

Parameter Name	Unit	Parameter Structure
Wear Force	Newton	$X_1 \rightarrow$ Input
Wear Time	Minute	$X_2 \rightarrow$ Input
Fired Temperature	ºC	$X_3 \rightarrow$ Input
Fired Time	Hour	$X_4 \rightarrow$ Input
Wear Volume	mm3	$Y_1 \rightarrow$ Output

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). The parameter combination was determined (Table 2). The correlation 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.

Table 2. Model Test Data Set and Training Data Sets Measures for Porcelain

		MAPE	MAE	RMSE	R^2
Linear Regression	Training Data Set	1,1111	2,0768	2,5458	0,8905
	Model Test Data Set	0,0850	1,3321	1,5803	0,8813
Interaction Regression	Training Data Set	0,1816	1,4862	1,7335	0,9492
	Model Test Data Set	0,0475	0,7136	0,9507	0,9571
Robust Regression	Training Data Set	0,5888	2,0429	2,5757	0,8879
	Model Test Data Set	0,0973	1,5243	1,8876	0,8307
Stepwise Regression	Training Data Set	0,1901	1,5313	1,7751	0,9468
	Model Test Data Set	0,0505	0,7723	0,9973	0,9527

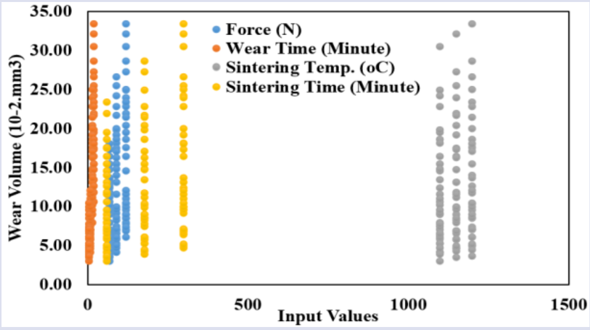

Figure 3. Scatter Plot Between Input and Output Data.

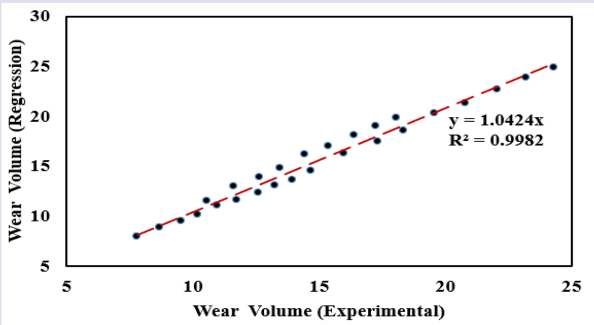

Figure 4. R^2 graph of regression model results produced for 15-minute wear time with the model training set and real experimental results.

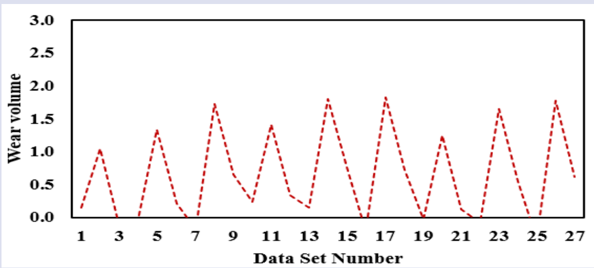

Figure 5. Actual Value and Output Differences (Error) Graph of regression model results produced for 15-minute wear time with the model training set and real experimental results.

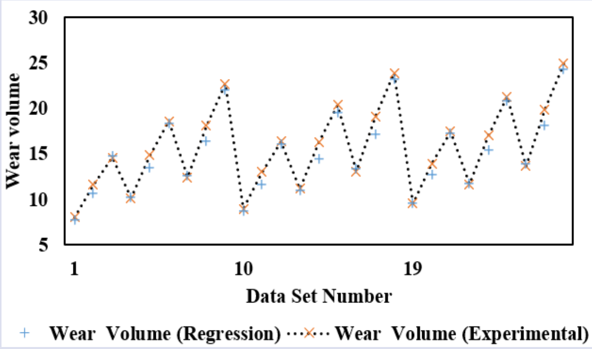

Figure 6. Comparison graphs of Actual Value and Outputs Graph of regression model results produced for 15-minute wear time with the model training set and real experimental results.

Before the regression 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 regression 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".

Figure 3 shows the Scatter Plot Between Input and Output Data. The "model training set all data" graphs of Support vector machines model results produced for 15-minute time with the model training set are shown in Figure 4,5,6. As can be seen from the figures and Table 2, very successful results were obtained in the study conducted with regression.

In this study, the factors affecting the wear behaviour of porcelain ceramics were analysed quantitatively using regression. According to the machine learning analysis performed in this study, the applied load (X1) and application time (X2) in the wear test, and the sintering temperature (X3) and time (X4) are the most critical parameters in estimating the amount of wear(Y). While creating the regression, the training data set was divided into 4 parts (Training, Testing, Validation and All data set).

15-minute wear time of the data was used for testing and 4 different regression methods (Linear Regression, Robust Regression, Interaction Regression and Stepwise Regression) were used. The best result was obtained in Interaction Regression and Stepwise Regression. 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 0,9571 and 0,9527 for 15-

minute wear time. The MAPE (0,0475 and 0,0505), MAE (0,7136 and 0,7723) and RMSE (0,9507 and 0,9973) values obtained for the regression model 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. The R^2 value was found to be 0.9779 for the model test data and 0.9492 for all test data from the graphs of the regression produced results and real experimental results.

As a result, regression models have shown acceptable success in predicting the wear properties of ceramic materials and indicate that they can be used in other areas of materials science.

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 regression approach, the patterns of an experimental study.

In this study, a highly sensitive machine learning algorithm based on regression is introduced to predict the wear properties of porcelain ceramics. Factors affecting wear were quantitatively analysed using regression. According to the machine learning analysis performed in this study, the applied load (X1) and application time (X2) in the wear test, and the sintering temperature (X3) and time (X4) 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.
- 15-minute wear time of the data was used for testing and 4 different regression methods (Linear Regression, Robust Regression, Interaction Regression and Stepwise Regression) were used. The best result was obtained in Interaction Regression and Stepwise Regression.
- 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 0,9571 and 0,9527 for 15-minute wear time.
- The MAPE (0,0475 and 0,0505), MAE (0,7136 and 0,7723) and RMSE (0,9507 and 0,9973) values obtained for the regression model for 15 minute and are within the quite acceptable range.
- The R^2 value was found to be 0.9779 for the model test data and 0.9492 for all test data from the graphs of the Support vector machines produced results and real experimental results.

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.

Declaration of Interest

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.

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