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A Supervised Machine Learning Model for Dental Crowns Material Design for Manufacturing

Adel Osama [a*], Noha Fouda [b], Mohamed T. Eraky [c]

[a]*Production Engineering and Mechanical Design Department, Faculty of Engineering, Mansoura University, P.O. 35516, Mansoura, Egypt;*
[b]*Production Engineering and Mechanical Design Department, Faculty of Engineering, Mansoura University, Mansoura, P.O. 35516, Egypt;*
[c]*Production Engineering and Mechanical Design Department, Faculty of Engineering, Mansoura University, Mansoura, P.O. 35516, Egypt;*

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ABSTRACT

Dental crowns material design is an urgent matter for dental manufacturers. Therefore, evaluating the composition and properties for implementing a decision-making model in materials design is a topical problem in the field of the design for manufacturing**.** The article aims to develop a supervised machine learning model for dental crowns material design. The proposed model is a function of two phases. The first phase that is an integration of two methods: FUZZY-ENTROPY and FUZZY-TOPSIS filters the submitted dataset and determines the most appropriate dental crowns material, and the second phase is a supervised machine learning model in which a filtered dataset that is a function of the material composition of zirconia(ZrO2) with different stabilizers at different sintering temperatures as inputs, and physical and mechanical properties of the different types of stabilized zirconia as outputs is fed into the model, trained using regression analysis and validated using mean average percentage error and root mean square error. The model can predict the required physical and mechanical properties in case of feeding the model with material composition and required sintering temperature(direct problem), and the model also can predict the required material composition in case of feeding the model with available physical and mechanical properties(inverse problem). Our model provides support and help for dental manufacturers to optimize dental crowns material**.**

1. Introduction

Teeth damage has strong implications in phonetics, aesthetics, and mastication processes. The repair /replacement of damaged tissues is carried out using artificial materials, which should be able to withstand the severe mechanical, chemical, and thermal oral requirements. According to ISO 6872, dental ceramic is an inorganic, non-metallic material which is specifically formulated for use when processed according to the manufacturers' instructions to form the whole or part of a dental restoration or prosthesis[19].

Dental ceramics are widely used for this purpose especially zirconia which is classified as high toughness bioceramic material[10]. Pure ZrO_2 powder has a monoclinic crystal structure at room temperature and transforms to tetragonal between 1167º C and 2367º C and then cubic zirconia at temperatures above 2367º C. The transition from tetragonal to monoclinic phase results in a 3% to 5% volume increase, which produces micro-cracks in bulk zirconia samples and a reduction in strength and toughness. under this condition, pure zirconia would be useless for dental restorative applications. However, the addition of some metallic oxides(stabilizers) to zirconia has been found to keep the tetragonal phase from transforming into a monoclinic phase as zirconia cools to room temperature, preventing the development of micro-cracks and preserving the mechanical properties of the tetragonal phase[9,14,15].

*Corresponding author. Tel.: +2 01124464713
E-mail address: mec.eng@std.mans.edu.eg

The Types of oxide include magnesia (MgO), Calcia (CaO), yttria (Y_2O_3), Alumina(Al_2O_3), and ceria (Ce_2O_3). The oxide-doped zirconia is termed stabilized zirconia[11].

Therefore, the study effect of the concentration of stabilizer on physical and mechanical properties is an urgent matter in dental materials design. In this regard, several scientific works in studying the effect of stabilizers concentration and sintering temperature on physical and mechanical properties are analyzed below in addition to some other works in developing automated materials selection and design in smart manufacturing. Volodymyr et al.[2] analyzed the microstructure, strength, and fracture behavior for ZrO_2 ceramics stabilized with 3-8 mol%Y_2O_3 sintered at 1550º C for 2h and announced that with an increase in Y_2O_3 content, the average size of grains decreased and minimum flexural strength for 5YSZ is associated with maximum fraction of cubic ZrO_2 phase.

Hidekazu et al.[12] evaluated the mechanical properties of yttria-based zirconia and ceria-based composite zirconia as dental materials and announced that ceria-based composite zirconia did not exhibit translucency, but it can be applied to long-span bridges due to its excellent fracture toughness and flexural strength. In the flexural strength test, sample 3YSZ (yttria-based zirconia) containing 0.26 wt% alumina exhibited the highest values among the respective zirconia samples, with biaxial flexure strength of 1384 MPa.

Noor et al.[1] investigated the effect of sintering temperature on the mechanical properties of zirconia fabricated through colloidal and cold isostatic pressing and announced that Sintering temperature, not autoclave aging, appeared as the sole factor affecting the mechanical performance of the zirconia sample. Based on the other mechanical test results, they concluded that the sintering temperature of 1500◦C could be considered an appropriate temperature for sintering zirconia restorations because of acceptable flexural strength, fracture toughness, and hardness. It is known that sintering temperatures beyond 1600º C and longer dwell times are not suitable for improving mechanical properties, as samples may get burnt out and become brittle[13].

Ivan et al.[7]announced an automated material selection method based on regression analysis for solving the direct and inverse problems of rational material selection based on phase composition and physical and mechanical properties.

Mohamed et al.[8] developed a framework for welding process selection based on optimization techniques such as FUZZY-AHP and FUZZY-TOPSIS.

Lizheng et al.[18] prepared a good bioceramic material that consists of 91wt.% of ZrO_2(3Y),6wt.% of Al_2O_3,3wt.% of SiO_2 powders, after they use it in manufacturing dental crowns by VAT photopolymerization which is an additive manufa-cturing process, and the manufactured part could meet the performance requirements of all dental implants and achieve excellent biocompatibility.

Hezhen et al.[19] prepared a bioceramic material and its major composition is 3mol.% of yttria stabilized zirconia and its properties are nearly acceptable but they announced that the clinically accepted dental crowns are functions of productivity and delivery time, dimensional accuracy, surface quality and aesthetic behaviour .

The target of this study is to design a machine learning model that can predict the required physical and mechanical properties of dental crowns material in case of feeding the model with material composition and required sintering temperature (direct problem), and it can also predict the required material composition in case of feeding the model with available physical and mechanical properties (inverse problem), and the previous targets have been formulated in two major stages. Firstly, Data was prepared and filtered using FUZZY-ENTROPY, and FUZZY-TOPSIS. Secon-dly, filtered data has been submitted to a machine learning algorithm in which direct and inverse problems of rational material selection have been solved which is based on phase composition, sintering temperatures, and physical and mechanical properties. Finally, matrix dependencies for evalu-ating physical and mechanical properties by phase composition and sintering temperatures, and vice versa, should be validated by error analysis. Overall, the proposed model will help dental manufacturers optimize the design and selection of dental crowns material.

2. Materials and Methods

2.1 General model

The proposed model is schematically represented in Figure 1,and its consequent stages include the design calculation.

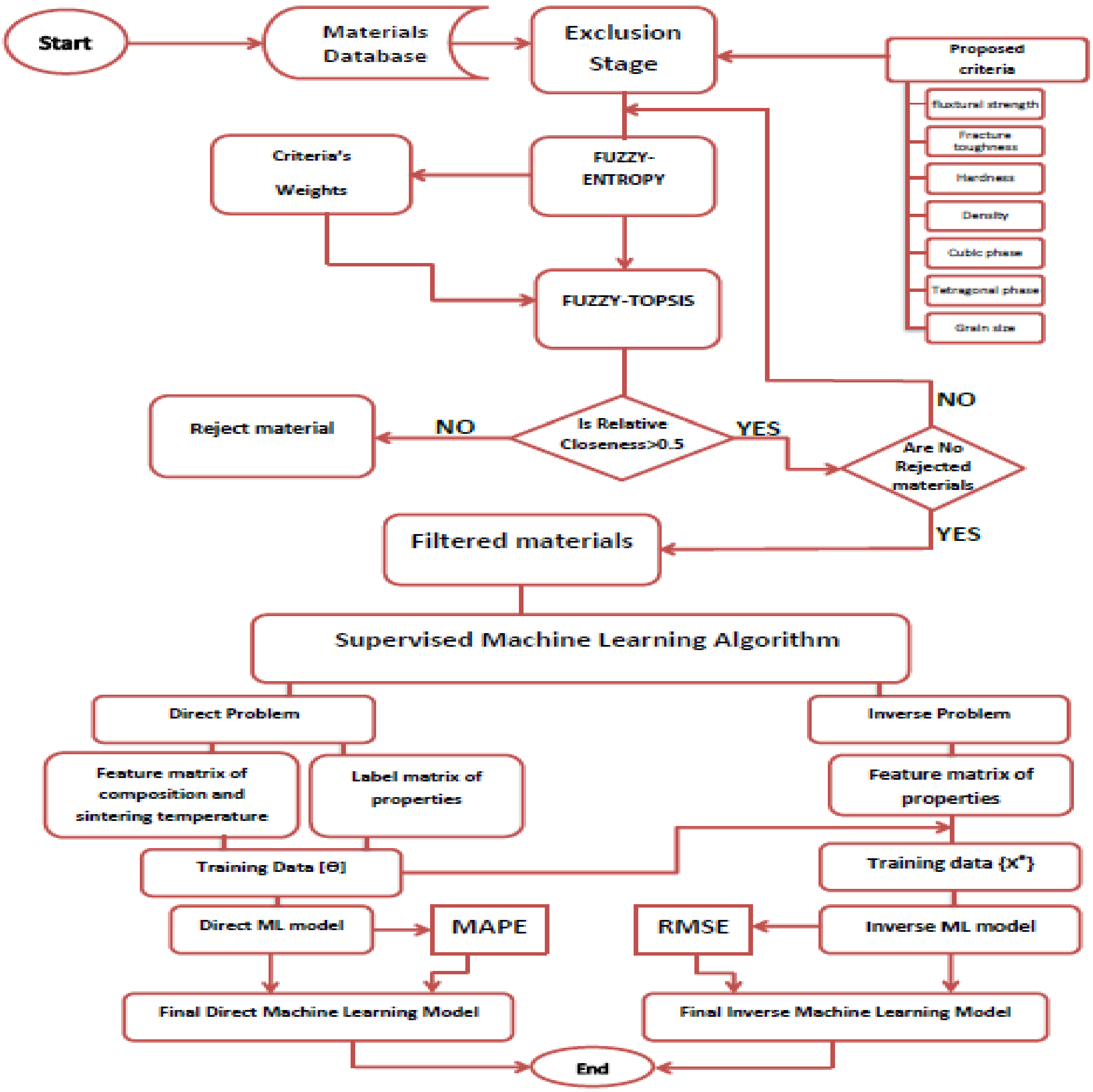

Figure 1. The scheme of the proposed model.

2.2 Data collection

The first step in our work is data collection which is represented in Table1 and Table2, we collect data for 35 materials which consist of zirconia and different Types of stabilizers(Y_2O_3, MgO, Ce_2O_3, Al_2O_3, CaO)with different preferable molar concentration at a specific range of sintering temperatures, range of sintering temperature is from 1400:1600 degree Centigrade forming a feature matrix(matrix of independent variables) with size 35 and diversity 7, then recording mechanical and physical properties for each of previous materials such as flexural strength, fracture toughness, hardness, density, tetragonal phase percentage, cubic phase percentage and grain size forming a label matrix (matrix of dependent variables) with size 35 and diversity 7.

Table 1. The chemical composition and sintering temperature range of proposed materials that are taken from following researches[1,2,12,13].

Material TYPE	Sintering temperature °C	wt.% of Percent ZrO2	wt.% of Percent Y2O3	wt.% of Percent CaO	wt.% of Percent MgO	wt.% of Percent Ce2O3	wt.% of Percent Al2O3
	x1	x 2	x3	x 4	x 5	x 6	x 7
TYPE1	1400	95.75	4.15	0.05	0	0	0
TYPE2	1450	95.4	4.5	0.05	0	0	0
TYPE3	1500	94.8	5.1	0.05	0	0	0
TYPE4	1550	94.4	5.5	0.05	0	0	0
TYPE5	1600	93.9	6	0.05	0	0	0
TYPE6	1400	93.5	6.4	0.05	0	0	0
TYPE7	1450	93.2	6.7	0.05	0	0	0
TYPE8	1500	92.9	7	0.05	0	0	0
TYPE9	1550	92.65	7.25	0.05	0	0	0
TYPE10	1600	91.9	8	0.05	0	0	0
TYPE11	1400	90.65	9.25	0.05	0	0	0
TYPE12	1450	90.5	9.4	0.05	0	0	0
TYPE13	1500	90.3	9.6	0.05	0	0	0
TYPE14	1550	90.1	9.8	0.05	0	0	0
TYPE15	1600	89.9	10	0.05	0	0	0
TYPE16	1400	97.12	0	0.08	2.8	0	0
TYPE17	1450	97.02	0	0.08	2.9	0	0
TYPE18	1500	96.92	0	0.08	3	0	0
TYPE19	1550	96.82	0	0.08	3.1	0	0
TYPE20	1600	96.72	0	0.08	3.2	0	0
TYPE21	1400	83.75	0	0	0	16	0.25
TYPE22	1450	83.55	0	0	0	16.2	0.25
TYPE23	1500	83.35	0	0	0	16.4	0.25
TYPE24	1550	83.15	0	0	0	16.6	0.25
TYPE25	1600	82.95	0	0	0	16.8	0.25
TYPE26	1400	23.7	1.3	0.05	0	0	74.95
TYPE27	1450	23.6	1.3	0.05	0	0	75.05
TYPE28	1500	23.5	1.3	0.05	0	0	75.15
TYPE29	1550	23.4	1.3	0.05	0	0	75.25
TYPE30	1600	23.2	1.3	0.05	0	0	75.45
TYPE31	1400	94	0	6	0	0	0
TYPE32	1450	93	0	7	0	0	0
TYPE33	1500	92.5	0	7.5	0	0	0
TYPE34	1550	92	0	8	0	0	0
TYPE35	1600	91.9	0	8.1	0	0	0

Table 2. The mechanical and physical properties of proposed materials that are taken from following researches[1,2,12,13].

Material TYPE	Flexural strength MPa	Fracture Toughness Mpa.m$^{0.5}$	Vickers Hardness GPa	Density Kg/m3	Cubic Phase %	Tetragonal Phase %	Grain Size micron
	y1	y 2	y3	y 4	y 5	y 6	y 7
TYPE1	650	7	15.7	5.76	5	95	0.5
TYPE2	900	8	15.5	5.82	7	93	0.54
TYPE3	1000	9	15.7	5.88	8	92	0.58
TYPE4	900	13	15.6	5.9	9	91	0.6
TYPE5	700	10	15.8	6.07	10	90	0.63
TYPE6	600	4	14.7	5.7	20	80	0.65
TYPE7	850	5	14.5	5.77	21	79	0.68
TYPE8	900	6	14.7	5.83	22	78	0.7
TYPE9	850	7	14.6	5.89	23	77	0.75
TYPE10	600	6	14.8	6.02	25	75	0.8
TYPE11	550	3.5	13.7	5.69	45	55	0.85
TYPE12	650	4	13.5	5.75	46	54	0.86
TYPE13	800	5	13.7	5.8	47	53	0.88
TYPE14	650	6	13.6	5.87	48	52	0.9
TYPE15	600	4	13.8	5.99	50	50	1
TYPE16	610	10	11	5.66	45	55	30
TYPE17	615	10.2	11.2	5.68	46	54	32
TYPE18	620	10.4	11.4	5.7	47	53	34
TYPE19	610	10.6	11.6	5.73	48	52	37
TYPE20	600	11	12	5.75	50	50	40
TYPE21	520	11	11	5.92	5	95	2
TYPE22	520	11.2	11.2	5.93	7	93	2.2
TYPE23	530	11.4	11.4	5.95	9	91	2.4
TYPE24	550	11.7	11.6	6.1	11	89	2.7
TYPE25	540	12	12	6.2	13	87	3
TYPE26	730	5	17.2	4.1	1	99	1.5
TYPE27	735	5.5	17.3	4.15	2	98	1.52
TYPE28	740	6	17.35	4.2	3	97	1.53
TYPE29	760	7	17.4	4.25	4	96	1.6
TYPE30	750	6.5	17.3	4.3	5	95	1.65
TYPE31	1000	5.2	0.5	5	45	55	0.16
TYPE32	1050	5.4	0.8	5.2	46	54	0.167
TYPE33	1100	5.6	1	5.4	47	53	0.17
TYPE34	1150	6	1.5	5.7	48	52	0.175
TYPE35	1200	5.8	1.4	5.3	50	50	0.18

2.3 Data preparation

The second step in our work is data preparation and filtration, we optimize the proposed 35 materials(Label matrix) by two methods (the FUZZY-ENTROPY)method for calculating weights of criteria and (the FUZZY-TOPSIS)method for material ranking, we claim that material is rejected if its relative closeness index less than 0.5and when we apply that, five material types are rejected in the first trial, ten material types are rejected in a second trial, one material type is rejected in third trial and when applying the fourth trial , no material rejection occurs which implies that data is prepared, filtered. The filtered data contains nineteen materials which are a function of % wt zirconia, % wt stabilizer, and specific sintering temperature. The consequent stages of data preparation are previewed below:

Entropy Weight Method(EWM). [5] In this method, m indicators and n samples are set in the evaluation, and the measured value of the ith samples for the jth indicators is recorded as yij , first step is the standardization of measured values, the standardized value of the ith sample in jth indicator the is denoted as Pij, and its calculation method is as follows:

$$P_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}}, \qquad (1)$$

In the EWM, the entropy value Ej of the jth index is Calculated as follows:

$$E_j = -\frac{\sum_{i=1}^{n} (p_{ij} * ln(p_{ij}))}{ln(n)} \qquad (2)$$

In the EWM, the calculation method of weight wj is as follows:

$$W_j = \frac{1 - E_j}{\sum_{J=1}^{m} (1 - E_j)} \qquad (3)$$

The weights calculated from EWM is used in FUZZY-TOPSIS method to get the most suitable materials ,the common algorithm of TOPSIS for ranking and selection includes the following seven steps [21] :

Step1: Create a decision or evaluation matrix ***D***.

The matrix consists of n samples (A1,…, Am) and m criteria (y1,…, ym), with its element yij , where i =(1 ,…………. , n) and j = (1 , ……………. , m):

Step 2: Construct the normalized decision matrix ***R***. :

$$r_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} {y_{ij}}^2}} \qquad (5)$$

$$R = \begin{bmatrix} r_{11} & \cdots & r_{1m} \\ \vdots & \vdots & \vdots \\ r_{n1} & \cdots & r_{nm} \end{bmatrix}_{nXm} \qquad (6)$$

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Step 3: Construct the weighted normalized decision matrix ***V*** :

$$[\mathrm{V}] = [W_j r_{ij}] \qquad (7)$$

A set of weights W=(w_1,………,w_m)and $\sum_{j=1}^{m} w_j = 1, where\ w_j > 0,\ \ j =$
$1, \dots \dots, m\ is\ given\ to\ the\ coeereponing\ criterion\ y_j$, Where j=1,……..,m. The matrix V=[$w_j r_{ij}$] is calculated by multiplying the elements as each column of the matrix R by their associated weights $w_j, j = 1, \dots \dots, m$

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1m} \\ \vdots & \vdots & \vdots \\ v_{n1} & \cdots & v_{nm} \end{bmatrix}_{nXm} \qquad (8)$$

Step 4 : determination of the positive ideal and negative –ideal solution V^+(PIS) and V^-(NIS),respectively.

PIS is defined as :

$$V^+ = \{{v_1}^+, \dots \dots, {v_m}^+\} = \left\{\left(\max_i v_{ij} | j \in J\right), \left(\left(\min_i v_{ij} | j \in J'\right)\right)\right\} \qquad (9)$$

and NIS is defined as :

$$V^- = \{{v_1}^-, \dots \dots, {v_m}^-\} = \left\{\left(\min_i v_{ij} | j \in J\right), \left(\left(\max_i v_{ij} | j \in J'\right)\right)\right\} \qquad (10)$$

where j is associated with the benefit criteria and j' is associated with the cost criteria ,on criterion $y_j, where\ j = 1, \dots \dots, m\ for\ all\ samples\ i = 1, \dots \dots, n.$

Step5: Calculate the separation measure between alternative A_i
(samples),
${s_i}^+ and\ {s_i}^-, and\ the\ ideal\ and\ the\ negativ\ ideal\ solutions, resp$
The separation measure or distance between

$$D = \begin{bmatrix} y_{11} & \cdots & y_{1m} \\ \vdots & \vdots & \vdots \\ y_{n1} & \cdots & y_{nm} \end{bmatrix}_{nXm} \qquad (4)$$

alternatives (samples) and the PIS can be measured by n-dimensional Euclidean distance as follows

$${S_i}^+ = \sqrt{\sum_{j=1}^{m} (V_{ij} - {V_J}^+)^2} \qquad (11)$$

for alternatives A_i , i=1,…….,n

The separation measure or distance between alternatives (samples) and the NIS can be illustrated as follows:

$$S_i^- = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_J^-)^2} \qquad (12)$$

for alternatives A_i ,i=1,…….,n

Step 6: Calculate the relative closeness C_i^* of alternatives A_i, i=1,…….,n, the relative closeness or ranking index of samples is defined as follows:

$$\mathbf{C_i}^* = \frac{\mathbf{S_i}^-}{\mathbf{S_i}^+ + \mathbf{S_i}^-} \qquad (13)$$

The larger the index value is, the better is the performance of the alternative. The relative closeness is the judgment rule of the decision in FUZZY- TOPSIS[3].

Step 7: Rank the preference order of all alternatives.

A set of alternatives A_i , i = 1,…, n, can now be preference ranked according to the descending order of the value of c_i^*. In general, the selection should be the alternative with the highest value of the relative closeness, but it is claimed that if relative closeness of alternative is less than 0.5 ,it is rejected and previous steps are repeated until the trial in which all alternative is greater than or approaches 0.5,then at that trial data is prepared and ready for machine learning model .

2.2 Data prediction

The third step in our work is feeding data into machine learning algorithm in which filtered data is normalized then trained by regression analysis and after that machine learning model is formed which its target is required data prediction .when input feature matrix is fed into machine learning model ,the model will predict the target label matrix .then we calculate the error percentage using MAPE(mean average percentage error) which is preferred to be less than 50 percent to be accepted.

2.2.1Direct problem

This is a normalized feature matrix of phase composition and sintering temperature :

$$\bar{X}_{i,j} = \frac{x_{ij}}{\mathrm{Max}(x_j)} \qquad (14)$$

This is a normalized label matrix of physical and mechanical properties :

$$\bar{Y}_{i,j} = \frac{y_{ij}}{\mathrm{Max}(y_j)} \qquad (15)$$

the direct problem is the evaluation of the impact of material's phase composition and sintering temperature on its physical and mechanical properties based on following matrix equation:

$$[\bar{X}][\Theta] = [\bar{Y}] \qquad (16)$$

the weighted decision matrix[Θ] is evaluated using the following equation :

$$[\Theta] = (\bar{X}^T\bar{X})^{-1}\bar{X}^T\bar{Y} \qquad (17)$$

The unknown matrix$\left[\bar{\bar{Y}}\right]$ of physical and mechanical properties can be evaluated from the following equation:

$$[\bar{\bar{Y}}] = [\bar{X}][\Theta] \qquad (18)$$

The estimation accuracy can be estimated by mean absolute percentage error[16] which is indicated as follows :

$$MAPE_j = \frac{\mathbf{1}}{\boldsymbol{n}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \left(\left| \frac{\bar{\bar{y}}_{ij} - \bar{y}_{ij}}{\bar{y}_{ij}} \right| \right) \qquad (19)$$

the less the mean absolute percentage error ,the higher the estimation accuracy for the direct problem. The true values can be estimated from following equation:

$$\text{True value} = \frac{Predicted\ value}{1-MAPE} \quad (20)$$

2.2.2 Inverse problem

This inverse problem is more valuable for practical purposes in which the predicted label matrix is indicated as follows:

$$[\hat{X}] = \begin{bmatrix} x_{10} & \cdots & x_{1d} \\ \vdots & \ddots & \vdots \\ x_{n0} & \cdots & x_{nd} \end{bmatrix}_{nx(d+1)} \qquad (21)$$

Matrix is rectangular with dimension n x (d+1),where n total number of considered materials and d is total number of phase compositions and sintering temperature, we also add column for bias in which each value is equal one.

This is a normalized feature matrix of physical and mechanical properties :

$$[\bar{Y}] = \begin{bmatrix} y_{11} & \cdots & y_{1m} \\ \vdots & \ddots & \vdots \\ y_{n1} & \cdots & y_{nm} \end{bmatrix}_{nxm} \qquad (22)$$

This is a governing equation to get the label predicted matrix :

$$\left[\hat{\bar{X}}\right] = (([\theta][\theta^T])^{-1}[\theta][\bar{Y}]^T)^{\,T} \qquad (23)$$

The estimation accuracy can be estimated by root mean square error[16] which is indicated as follows:

$$RMSE_K = \sqrt{\frac{\sum_{i=1}^{n}(\bar{\hat{x}}-\bar{x})^2}{n}} \qquad (24)$$

$RMSE_k$ is for a (d) attributes where k=(1,…….,d)

$$NRMSE_K = \frac{RMSE_K}{Max(X_K) - Min(X_K)} \qquad (25)$$

$NRMSE_k$[17] is a way to gain better understanding of RMSE for a (d) attributes where k=(1,…….,d).

3. Results

3.1. results of data preparation stage

The results of data preparation stages are represented in Table 3(which includes evaluation of weights),Table4,Table5,Table6 and Table7 (which include FUZZY-TOPSIS ranking and evaluation of 35 proposed materials),Table8,Table9and Table10 include filtered datasets that are submitted to supervised machine learning model.

Table 3. Evaluation of weights of 7 criteria which represents mechanical and physical properties of samples.

Trial number	W1	W2	W3	W4	W5	W6	W7
	y1	y 2	y3	y 4	y 5	y6	y 7
Trial 1	0.0168	0.0357	0.0667	0.0034	0.1633	0.0185	0.6956
Trial 2	0.0365	0.0781	0.1619	0.0082	0.3939	0.0339	0.2874
Trial 3	0.0453	0.0921	0.3323	0.0019	0.2776	0.0485	0.2023
Trial 4	0.0505	0.1028	0.2880	0.0013	0.3162	0.0528	0.1883

Table 4. This is *a TOPSIS evaluation of 35 proposed materials(trial one).*

Material TYPE Trial 1	si^+	si^-	ci*	Rank
TYPE1	0.3422	39.5000	0.99141	6
TYPE2	0.3818	39.4600	0.99042	7
TYPE3	0.4215	39.4200	0.98942	8
TYPE4	0.4414	39.4000	0.98892	9
TYPE5	0.4712	39.3700	0.98817	10
TYPE6	0.4907	39.3500	0.98768	11
TYPE7	0.5206	39.3200	0.98693	12
TYPE8	0.5406	39.3000	0.98643	13
TYPE9	0.5905	39.2500	0.98518	14
TYPE10	0.6404	39.2000	0.98393	15
TYPE11	0.6901	39.1500	0.98268	16
TYPE12	0.7001	39.1400	0.98243	17
TYPE13	0.7200	39.1200	0.98193	18
TYPE14	0.7400	39.1000	0.98142	19
TYPE15	0.8400	39.0000	0.97891	20
TYPE16	29.8400	10.0001	0.25101	31

TYPE17	31.8400	8.0001	0.20081	32
TYPE18	33.8400	6.0001	0.15061	33
TYPE19	36.8400	3.0003	0.07531	34
TYPE20	39.8400	0.0432	0.00108	35
TYPE21	1.8404	38.0000	0.95381	26
TYPE22	2.0403	37.8000	0.94879	27
TYPE23	2.2403	37.6000	0.94377	28
TYPE24	2.5402	37.3000	0.93624	29
TYPE25	2.8402	37.0000	0.92871	30
TYPE26	1.3407	38.5000	0.96635	21
TYPE27	1.3606	38.4800	0.96585	22
TYPE28	1.3706	38.4700	0.96560	23
TYPE29	1.4405	38.4000	0.96384	24
TYPE30	1.4905	38.3500	0.96259	25
TYPE31	0.0163	39.8400	0.99959	1
TYPE32	0.0173	39.8330	0.99957	2
TYPE33	0.0184	39.8300	0.99954	3
TYPE34	0.0211	39.8250	0.99947	4
TYPE35	0.0249	39.8200	0.99937	5

Table 5. This is a TOPSIS evaluation of 35 proposed materials(trial two).

Material TYPE Trial 2	si^{+}	si^{-}	ci*	Rank
TYPE1	0.1121	0.1063	0.500	20
TYPE2	0.1073	0.1054	0.500	19
TYPE3	0.1049	0.1046	0.500	18
TYPE4	0.1024	0.1052	0.507	17
TYPE5	0.1004	0.1039	0.509	16
TYPE6	0.0785	0.1097	0.583	15
TYPE7	0.0761	0.1097	0.590	14
TYPE8	0.0736	0.1103	0.600	13
TYPE9	0.0717	0.1099	0.605	12
TYPE10	0.0683	0.1107	0.619	11
TYPE11	0.0366	0.1413	0.794	8
TYPE12	0.0357	0.1428	0.800	6
TYPE13	0.0347	0.1444	0.806	4
TYPE14	0.0344	0.1458	0.809	3
TYPE15	0.0390	0.1476	0.791	9
TYPE21	0.1338	0.0495	0.270	26
TYPE22	0.1344	0.0450	0.251	27
TYPE23	0.1357	0.0421	0.237	28
TYPE24	0.1405	0.0399	0.221	30
TYPE25	0.1462	0.0421	0.224	29
TYPE26	0.1327	0.0707	0.347	24
TYPE27	0.1307	0.0702	0.349	23
TYPE28	0.1286	0.0701	0.353	21
TYPE29	0.1275	0.0682	0.349	22
TYPE30	0.1263	0.0666	0.345	25
TYPE31	0.0421	0.1570	0.789	10
TYPE32	0.0407	0.1586	0.796	7
TYPE33	0.0396	0.1602	0.802	5
TYPE34	0.0380	0.1619	0.810	2
TYPE35	0.0380	0.1653	0.813	1

Table 6. This is a TOPSIS evaluation of 35 proposed materials(trial three).

Material TYPE Trial 3	si^{+}	si^{-}	ci*	Rank
TYPE1	0.0809	0.0891	0.52	15
TYPE2	0.0769	0.0880	0.53	14
TYPE3	0.0750	0.0894	0.54	13
TYPE4	0.0728	0.0908	0.56	12
TYPE5	0.0720	0.0899	0.56	11
TYPE6	0.0603	0.0845	0.58	10
TYPE7	0.0578	0.0839	0.59	9
TYPE8	0.0554	0.0856	0.61	8
TYPE9	0.0537	0.0856	0.61	7
TYPE10	0.0526	0.0872	0.62	6
TYPE11	0.0382	0.0990	0.72	5
TYPE12	0.0373	0.0993	0.73	4
TYPE13	0.0350	0.1014	0.74	2
TYPE14	0.0345	0.1022	0.75	1
TYPE15	0.0394	0.1052	0.73	3
TYPE31	0.0902	0.0703	0.44	20
TYPE32	0.0882	0.0719	0.50	19
TYPE33	0.0869	0.0737	0.50	18
TYPE34	0.0838	0.0755	0.50	17
TYPE35	0.0844	0.0787	0.50	16

Table 7.*This is* a TOPSIS evaluation of 35 proposed materials(trial four).

Material TYPE Trial 4	si^{+}	si^{-}	ci*	Rank
TYPE1	0.0917	0.0765	0.5	19
TYPE2	0.0872	0.0757	0.5	18
TYPE3	0.0849	0.0771	0.5	17
TYPE4	0.0823	0.0796	0.5	15
TYPE5	0.0813	0.0777	0.5	16
TYPE6	0.0674	0.0736	0.5	12
TYPE7	0.0644	0.0735	0.5	10
TYPE8	0.0616	0.0753	0.6	8
TYPE9	0.0595	0.0757	0.6	7
TYPE10	0.0580	0.0776	0.6	6
TYPE11	0.0394	0.0971	0.7	5
TYPE12	0.0380	0.0980	0.7	3
TYPE13	0.0352	0.1003	0.7	2
TYPE14	0.0343	0.1016	0.7	1
TYPE15	0.0396	0.1050	0.7	4
TYPE32	0.0780	0.0799	0.5	14
TYPE33	0.0767	0.0819	0.5	13
TYPE34	0.0739	0.0840	0.5	11
TYPE35	0.0745	0.0877	0.5	9

Table 8. *This is a label table of physical and mechanical properties of filtered materials*

Filtered material TYPE	Flexural strength MPa	Fracture Toughness Mpa.m0.5	Vickers Hardness GPa	Density Kg/m3	Cubic Phase %	Tetragonal Phase %	Grain Size micron
	y1	y 2	y3	y 4	y 5	y 6	y 7
TYPE1	650	7	15.7	5.76	5	95	0.5
TYPE2	900	8	15.5	5.82	7	93	0.54
TYPE3	1000	9	15.7	5.88	8	92	0.58
TYPE4	900	13	15.6	5.9	9	91	0.6
TYPE5	700	10	15.8	6.07	10	90	0.63
TYPE6	600	4	14.7	5.7	20	80	0.65
TYPE7	850	5	14.5	5.77	21	79	0.68
TYPE8	900	6	14.7	5.83	22	78	0.7
TYPE9	850	7	14.6	5.89	23	77	0.75
TYPE10	600	6	14.8	6.02	25	75	0.8
TYPE11	550	3.5	13.7	5.69	45	55	0.85
TYPE12	650	4	13.5	5.75	46	54	0.86
TYPE13	800	5	13.7	5.8	47	53	0.88
TYPE14	650	6	13.6	5.87	48	52	0.9
TYPE15	600	4	13.8	5.99	50	50	1
TYPE32	1050	5.4	0.8	5.2	46	54	0.167
TYPE33	1100	5.6	1	5.4	47	53	0.17
TYPE34	1150	6	1.5	5.7	48	52	0.175
TYPE35	1200	5.8	1.4	5.3	50	50	0.18

Table 9. *This is a feature table of phase composition and sintering temperature of filtered materials*

Filtered material TYPE	Sintering temperature o C	wt.% of ZrO2	wt.% of Y2O3	wt.% of CaO	wt.% of MgO	wt.% of Ce2O3	wt.% of Al2O3
	x1	x 2	x3	x 4	x 5	x 6	x 7
TYPE1	1400	95.75	4.15	0.05	0	0	0.05
TYPE2	1450	95.4	4.5	0.05	0	0	0.05
TYPE3	1500	94.8	5.1	0.05	0	0	0.05
TYPE4	1550	94.4	5.5	0.05	0	0	0.05
TYPE5	1600	93.9	6	0.05	0	0	0.05
TYPE6	1400	93.5	6.4	0.05	0	0	0.05
TYPE7	1450	93.2	6.7	0.05	0	0	0.05
TYPE8	1500	92.9	7	0.05	0	0	0.05
TYPE9	1550	92.65	7.25	0.05	0	0	0.05
TYPE10	1600	91.9	8	0.05	0	0	0.05
TYPE11	1400	90.65	9.25	0.05	0	0	0.05
TYPE12	1450	90.5	9.4	0.05	0	0	0.05
TYPE13	1500	90.3	9.6	0.05	0	0	0.05
TYPE14	1550	90.1	9.8	0.05	0	0	0.05
TYPE15	1600	89.9	10	0.05	0	0	0.05
TYPE32	1450	93	0	7	0	0	0
TYPE33	1500	92.5	0	7.5	0	0	0
TYPE34	1550	92	0	8	0	0	0
TYPE35	1600	91.9	0	8.1	0	0	0

Table 10. *This is a feature table of phase composition and sintering temperature of filtered materials after exclusion of zero columns.*

Filtered material TYPE	Sintering temperature o C	wt.% of ZrO2	wt.% of Y2O3	wt.% of CaO	wt.% of Al2O3
	x1	x 2	x3	x 4	x 7
TYPE1	1400	95.75	4.15	0.05	0.05
TYPE2	1450	95.4	4.5	0.05	0.05
TYPE3	1500	94.8	5.1	0.05	0.05
TYPE4	1550	94.4	5.5	0.05	0.05
TYPE5	1600	93.9	6	0.05	0.05
TYPE6	1400	93.5	6.4	0.05	0.05
TYPE7	1450	93.2	6.7	0.05	0.05
TYPE8	1500	92.9	7	0.05	0.05
TYPE9	1550	92.65	7.25	0.05	0.05
TYPE10	1600	91.9	8	0.05	0.05
TYPE11	1400	90.65	9.25	0.05	0.05
TYPE12	1450	90.5	9.4	0.05	0.05
TYPE13	1500	90.3	9.6	0.05	0.05
TYPE14	1550	90.1	9.8	0.05	0.05
TYPE15	1600	89.9	10	0.05	0.05
TYPE32	1450	93	0	7	0
TYPE33	1500	92.5	0	7.5	0
TYPE34	1550	92	0	8	0
TYPE35	1600	91.9	0	8.1	0

3.2. results of data prediction stage

This is a normalized matrix of phase composition and sintering temperature :

$$[\bar{\mathbf{X}}] = \begin{bmatrix} 1 & 0.8750 & 1.0000 & 0.4150 & 1.0000 & 0.0063 \\ 1 & 0.9063 & 0.9963 & 0.4500 & 1.0000 & 0.0063 \\ 1 & 0.9375 & 0.9901 & 0.5100 & 1.0000 & 0.0063 \\ 1 & 0.9688 & 0.9859 & 0.5500 & 1.0000 & 0.0063 \\ 1 & 1.0000 & 0.9807 & 0.6000 & 1.0000 & 0.0063 \\ 1 & 0.8750 & 0.9765 & 0.6400 & 1.0000 & 0.0063 \\ 1 & 0.9063 & 0.9734 & 0.6700 & 1.0000 & 0.0063 \\ 1 & 0.9375 & 0.9702 & 0.7000 & 1.0000 & 0.0063 \\ 1 & 0.9688 & 0.9676 & 0.7250 & 1.0000 & 0.0063 \\ 1 & 1.0000 & 0.9598 & 0.8000 & 1.0000 & 0.0063 \\ 1 & 0.8750 & 0.9467 & 0.9250 & 1.0000 & 0.0063 \\ 1 & 0.9063 & 0.9452 & 0.9400 & 1.0000 & 0.0063 \\ 1 & 0.9375 & 0.9431 & 0.9600 & 1.0000 & 0.0063 \\ 1 & 0.9688 & 0.9410 & 0.9800 & 1.0000 & 0.0063 \\ 1 & 1.0000 & 0.9389 & 1.0000 & 1.0000 & 0.0063 \\ 1 & 0.9063 & 0.9817 & 0.0000 & 0.0000 & 0.7500 \\ 1 & 0.9375 & 0.9713 & 0.0000 & 0.0000 & 0.8750 \\ 1 & 0.9688 & 0.9661 & 0.0000 & 0.0000 & 0.9375 \\ 1 & 1.0000 & 0.9608 & 0.0000 & 0.0000 & 1.0000 \end{bmatrix}_{\mathbf{nx(d+1)}} , \quad (26)$$

we add a column for bias in which each value is one, and all normalized values are between 0 and 1.

. This is a normalized matrix of physical and mechanical properties:

$$[\bar{\mathbf{Y}}] = \begin{bmatrix} 0.5000 & 0.5385 & 0.9937 & 0.9489 & 0.1000 & 1.0000 & 0.5000 \\ 0.7500 & 0.6154 & 0.9810 & 0.9588 & 0.1400 & 0.9789 & 0.5400 \\ 0.8333 & 0.6923 & 0.9937 & 0.9687 & 0.1600 & 0.9684 & 0.5800 \\ 0.7500 & 1.0000 & 0.9873 & 0.9720 & 0.1800 & 0.9579 & 0.6000 \\ 0.5833 & 0.7692 & 1.0000 & 1.0000 & 0.2000 & 0.9474 & 0.6300 \\ 0.5000 & 0.3077 & 0.9304 & 0.9390 & 0.4000 & 0.8421 & 0.6500 \\ 0.7083 & 0.3846 & 0.9177 & 0.9506 & 0.4200 & 0.8316 & 0.6800 \\ 0.7500 & 0.4615 & 0.9304 & 0.9605 & 0.4400 & 0.8211 & 0.7000 \\ 0.7083 & 0.5385 & 0.9241 & 0.9703 & 0.4600 & 0.8105 & 0.7500 \\ 0.5000 & 0.4615 & 0.9367 & 0.9918 & 0.5000 & 0.7895 & 0.8000 \\ 0.4583 & 0.2692 & 0.8671 & 0.9374 & 0.9000 & 0.5789 & 0.8500 \\ 0.5417 & 0.3077 & 0.8544 & 0.9473 & 0.9200 & 0.5684 & 0.8600 \\ 0.6667 & 0.3846 & 0.8671 & 0.9555 & 0.9400 & 0.5579 & 0.8800 \\ 0.5417 & 0.4615 & 0.8608 & 0.9671 & 0.9600 & 0.5474 & 0.9000 \\ 0.5000 & 0.3077 & 0.8734 & 0.9868 & 1.0000 & 0.5263 & 1.0000 \\ 0.8750 & 0.4154 & 0.0506 & 0.8567 & 0.9200 & 0.5684 & 0.1670 \\ 0.9167 & 0.4308 & 0.0633 & 0.8896 & 0.9400 & 0.5579 & 0.1700 \\ 0.9583 & 0.4615 & 0.0949 & 0.9390 & 0.9600 & 0.5474 & 0.1750 \\ 1.0000 & 0.4462 & 0.0886 & 0.8731 & 1.0000 & 0.5263 & 0.1800 \end{bmatrix}_{\mathbf{nxm}} \quad (27)$$

According to the linear regression formula(17), the matrix of weighted factors has been evaluated :

$$[\theta] = \begin{bmatrix} \mathbf{2.3135} & \mathbf{-7.2691} & \mathbf{0.5087} & \mathbf{0.3983} & \mathbf{6.5352} & \mathbf{-2.7397} & \mathbf{-0.5754} \\ \mathbf{0.6259} & \mathbf{2.4957} & \mathbf{0.3613} & \mathbf{0.3932} & \mathbf{-1.1181} & \mathbf{0.5887} & \mathbf{0.3105} \\ \mathbf{-3.1535} & \mathbf{9.2603} & \mathbf{-0.5030} & \mathbf{-0.0357} & \mathbf{-8.5979} & \mathbf{4.5255} & \mathbf{0.7585} \\ \mathbf{-0.6507} & \mathbf{0.1791} & \mathbf{-0.3255} & \mathbf{-0.0256} & \mathbf{0.8236} & \mathbf{-0.4335} & \mathbf{0.7923} \\ \mathbf{1.2352} & \mathbf{-3.6385} & \mathbf{0.8047} & \mathbf{0.2488} & \mathbf{2.7272} & \mathbf{-1.0854} & \mathbf{-0.2939} \\ \mathbf{1.0862} & \mathbf{-3.6535} & \mathbf{-0.2909} & \mathbf{0.1511} & \mathbf{3.8253} & \mathbf{-1.6611} & \mathbf{-0.2833} \end{bmatrix}_{(d+1)xm} \tag{28}$$

The unknown normalized matrix of physical and mechanical properties can be evaluated from equation(18):

$$[\hat{\hat{Y}}] = \begin{bmatrix} \mathbf{0.6797} & \mathbf{0.5877} & \mathbf{0.9897} & \mathbf{0.9458} & \mathbf{0.0520} & \mathbf{1.0252} & \mathbf{0.4880} \\ \mathbf{0.6882} & \mathbf{0.6379} & \mathbf{0.9915} & \mathbf{0.9574} & \mathbf{0.0777} & \mathbf{1.0118} & \mathbf{0.5226} \\ \mathbf{0.6882} & \mathbf{0.6691} & \mathbf{0.9863} & \mathbf{0.9683} & \mathbf{0.1455} & \mathbf{0.9760} & \mathbf{0.5752} \\ \mathbf{0.6950} & \mathbf{0.7154} & \mathbf{0.9867} & \mathbf{0.9798} & \mathbf{0.1796} & \mathbf{0.9581} & \mathbf{0.6134} \\ \mathbf{0.6984} & \mathbf{0.7541} & \mathbf{0.9844} & \mathbf{0.9909} & \mathbf{0.2306} & \mathbf{0.9313} & \mathbf{0.6588} \\ \mathbf{0.6074} & \mathbf{0.4104} & \mathbf{0.9283} & \mathbf{0.9409} & \mathbf{0.4394} & \mathbf{0.8214} & \mathbf{0.6484} \\ \mathbf{0.6173} & \mathbf{0.4652} & \mathbf{0.9314} & \mathbf{0.9526} & \mathbf{0.4558} & \mathbf{0.8128} & \mathbf{0.6796} \\ \mathbf{0.6274} & \mathbf{0.5188} & \mathbf{0.9345} & \mathbf{0.9642} & \mathbf{0.4731} & \mathbf{0.8036} & \mathbf{0.7106} \\ \mathbf{0.6389} & \mathbf{0.5773} & \mathbf{0.9390} & \mathbf{0.9759} & \mathbf{0.4810} & \mathbf{0.7995} & \mathbf{0.7382} \\ \mathbf{0.6342} & \mathbf{0.5964} & \mathbf{0.9298} & \mathbf{0.9866} & \mathbf{0.5750} & \mathbf{0.7500} & \mathbf{0.8014} \\ \mathbf{0.5159} & \mathbf{0.1855} & \mathbf{0.8505} & \mathbf{0.9347} & \mathbf{0.9303} & \mathbf{0.5630} & \mathbf{0.8517} \\ \mathbf{0.5305} & \mathbf{0.2524} & \mathbf{0.8577} & \mathbf{0.9466} & \mathbf{0.9206} & \mathbf{0.5681} & \mathbf{0.8721} \\ \mathbf{0.5436} & \mathbf{0.3144} & \mathbf{0.8635} & \mathbf{0.9585} & \mathbf{0.9202} & \mathbf{0.5683} & \mathbf{0.8961} \\ \mathbf{0.5568} & \mathbf{0.3766} & \mathbf{0.8694} & \mathbf{0.9703} & \mathbf{0.9198} & \mathbf{0.5685} & \mathbf{0.9200} \\ \mathbf{0.5700} & \mathbf{0.4386} & \mathbf{0.8752} & \mathbf{0.9822} & \mathbf{0.9194} & \mathbf{0.5687} & \mathbf{0.9440} \\ \mathbf{0.8712} & \mathbf{0.4301} & \mathbf{0.0515} & \mathbf{0.8708} & \mathbf{0.9066} & \mathbf{0.5755} & \mathbf{0.1673} \\ \mathbf{0.9235} & \mathbf{0.4117} & \mathbf{0.0680} & \mathbf{0.8834} & \mathbf{0.9611} & \mathbf{0.5468} & \mathbf{0.1691} \\ \mathbf{0.9595} & \mathbf{0.4416} & \mathbf{0.0820} & \mathbf{0.8959} & \mathbf{0.9708} & \mathbf{0.5417} & \mathbf{0.1749} \\ \mathbf{0.9958} & \mathbf{0.4704} & \mathbf{0.0959} & \mathbf{0.9084} & \mathbf{0.9815} & \mathbf{0.5361} & \mathbf{0.1806} \end{bmatrix}_{nxm} \tag{29}$$

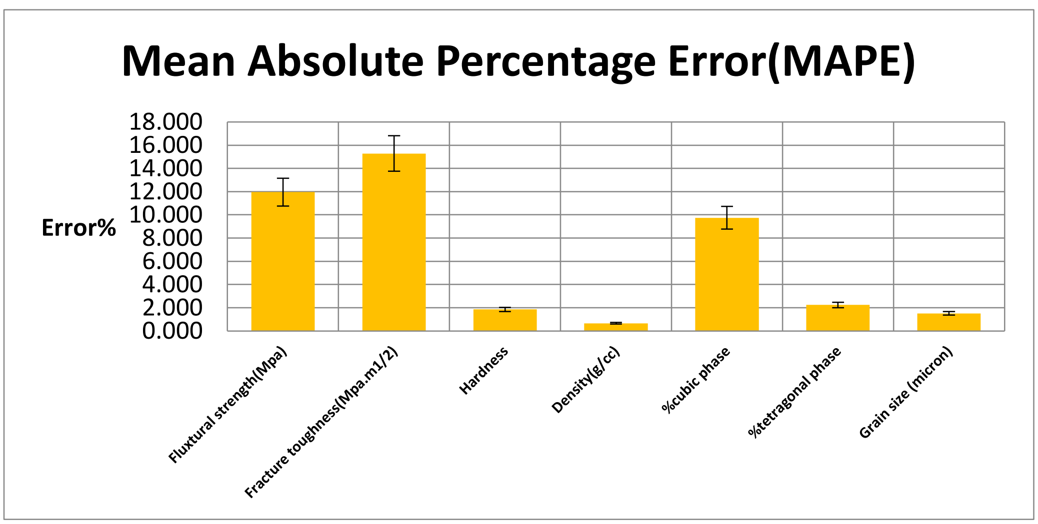

Figure 2. Graphical representation of mean absolute percentage error of physical and mechanical properties which is an indication of accuracy of direct problem model

The unknown normalized matrix of phase composition and sintering temperature in case of inverse problem can be evaluated from equation(22):

$$[\hat{\hat{X}}] = \begin{bmatrix} 1.0080 & 0.7991 & 1.0207 & 0.5130 & 1.0386 & -0.0241 \\ 0.9978 & 0.9373 & 0.9837 & 0.4488 & 0.9833 & 0.0207 \\ 0.9917 & 1.0077 & 0.9662 & 0.4599 & 0.9766 & 0.0212 \\ 0.9689 & 1.0809 & 0.9473 & 0.5428 & 0.9194 & 0.0553 \\ 1.0060 & 0.9536 & 0.9996 & 0.6274 & 1.0208 & -0.0084 \\ 1.0144 & 0.7903 & 1.0050 & 0.6669 & 1.0501 & -0.0291 \\ 1.0075 & 0.9070 & 0.9771 & 0.6076 & 1.0011 & 0.0126 \\ 1.0019 & 0.9587 & 0.9643 & 0.6223 & 0.9923 & 0.0158 \\ 1.0022 & 0.9777 & 0.9662 & 0.6879 & 0.9956 & 0.0129 \\ 1.0234 & 0.8886 & 1.0031 & 0.8248 & 1.0719 & -0.0417 \\ 0.9961 & 0.8756 & 0.9491 & 0.9535 & 1.0076 & -0.0051 \\ 0.9950 & 0.9272 & 0.9392 & 0.9302 & 0.9781 & 0.0231 \\ 0.9859 & 1.0120 & 0.9151 & 0.9087 & 0.9560 & 0.0360 \\ 0.9887 & 0.9949 & 0.9277 & 0.9888 & 0.9596 & 0.0351 \\ 1.0124 & 0.9522 & 0.9513 & 1.0825 & 1.0489 & -0.0299 \\ 0.9937 & 0.9026 & 0.9736 & -0.0003 & -0.0026 & 0.9962 \\ 1.0036 & 0.9375 & 0.9777 & -0.0024 & -0.0015 & 1.0050 \\ 1.0178 & 0.9836 & 0.9852 & 0.0062 & 0.0131 & 1.0048 \\ 0.9849 & 0.9889 & 0.9434 & -0.0035 & -0.0091 & 0.9939 \end{bmatrix} \quad (30)$$

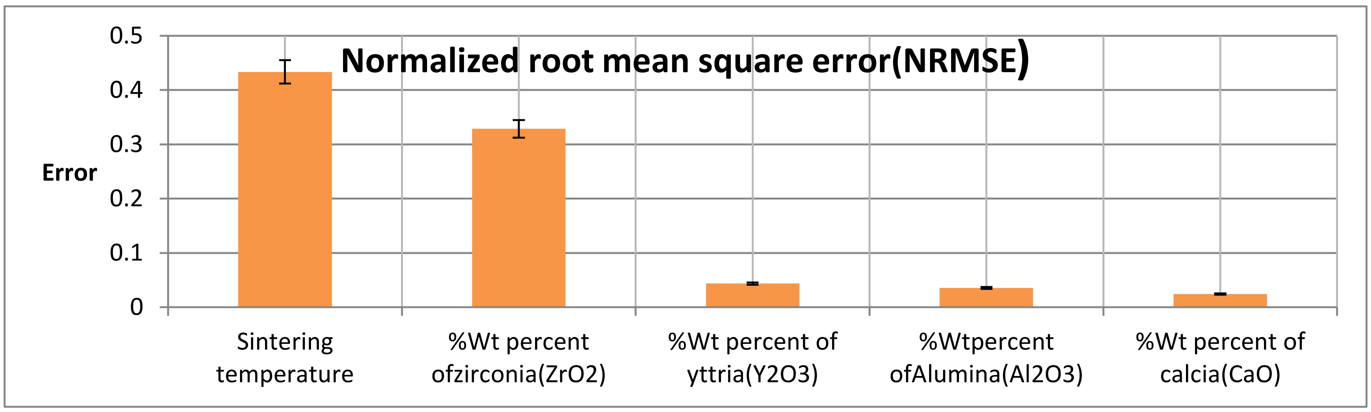

Figure 3. Graphical representation of root mean square error of phase composition and sintering temperature which is an indication of accuracy of inverse problem model

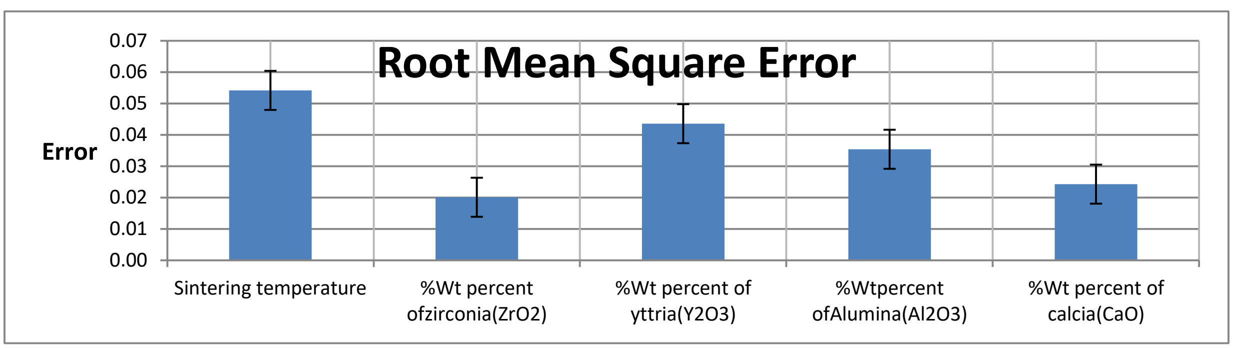

Figure 4. Graphical representation of Normalized root mean square error of phase composition and sintering temperature which is an indication of accuracy of inverse problem model.

Table 11. This is an indication of external data of commercial zirconia (Superfectzir) that manufactured by Aidite company .

	Sintering temperature o C	wt.% of ZrO2	wt.% of Y2O3	wt.% of CaO	wt.% of Al2O3
	x1	x 2	x3	x 4	x 7
Input composition	**1550**	**92**	**7.4**	**0.05**	**0.05**
Normalized input composition	**0.9688**	**0.9608**	**0.7400**	**1.0000**	**0.0063**

Table 12. This is an indication of mechanical prpperties of commercial zirconia (Superfectzir) that manufactured by Aidite company resulted from our model .

Filtered material TYPE	Flexural strength MPa	Fracture Toughness Mpa.m0.5	Vickers Hardness GPa	Density Kg/m3	Cubic Phase %	Tetragonal Phase %	Grain Size micron
	y1	y 2	y3	y 4	y 5	y 6	y 7
Normalized predicted properties	0.6505	0.5170	0.9375	0.9757	0.5518	0.7621	0.7448
MAPE	0.11957	0.15279	0.01852	0.00659	0.09745	0.02237	0.01517
Accuracy	0.880	0.847	0.981	0.993	0.903	0.978	0.985
Predicted Properties	780	6.72	14.81	5.92	27.59	72.40	0.74
True properties	885.93	7.93	15.08	5.95	30.56	74.05	0.75

Discussion

After a detailed analysis of the data preparation stage, it is observed that in Table 4 materials from TYPE16 to TYPE 20 are rejected as their relative closeness is much smaller than 0.5, in Table 5 materials from TYPE 21 to TYPE 30 are rejected, in Table 6 material with TYPE 31 is rejected, finally in table 7, no materials are rejected as all the materials are approaches 0.5 or higher hence they converge to positive ideal solution, and at that case we claim that data is prepared in tables 8,9 and 10, and are ready to be submitted into machine learning model. After a detailed analysis of the matrix [ϴ](26) that also indicated in table 13 in which values of positive numbers indicated that there is a direct proportional between inputs and outputs and values with negative numbers indicated that there is an inverse proportional between inputs and outputs, the following statements can be formulated. Value of 0.8236 indicates that an increase in yttria content significantly impacts an increase in cubic phase and therefore increases the translucency of dental crowns material, and also impacts a decrease in tetragonal phase, Value of -0.6507 indicates that an increase in yttria content impacts a decrease in flexural strength which corresponds to result of the study[2]. Value of -0.3255 indicates that an increase in yttria content impacts a decrease in hardness which corresponds to the result of the study[3]. Value of 1.0862 indicates that an increase in Calcia content impacts an increase in flexural strength which corresponds to the result of the study[4]. Figure 2 indicates the test accuracy of the direct model in which the maximum value of mean absolute percentage error does not exceed 16% which proves the reliability of the direct model. Figure 3 indicates the test accuracy of the inverse model in which the maximum value of root mean square error does not exceed 0.06 and Figure 4 indicates the test accuracy of the inverse model in which the maximum value of normalized root mean square error does not exceed 0.45 which proves the reliability of the inverse model**5**. We also use a commercial zirconia that its chemical composi-tion is indicated in table 11, then we use our model to predict its properties and the predicted values are indicated in table12 and we use equation 20 to predict the actual values that is also indicated in table12.

Table 13. This is an indication of the matrix theta

[ϴ]	Dv1	Dv2	Dv3	Dv4	Dv5	Dv6	DV7
	Flexural strength (Mpa)	Fracture toughness(Mpa .m1/2)	Hardness	Density(g/cc)	%cubic phase	%tetragonal phase	Grain size (micron)
(X0)Y-INTERCEPT	2.3135	-7.2691	0.5087	0.3983	6.5352	-2.7397	-0.5754
Sintering temperature	0.6259	2.4957	0.3613	0.3932	-1.1181	0.5887	0.3105
%Wt percentage of zirconia(ZrO2)	-3.1535	9.2603	-0.5030	-0.0357	-8.5979	4.5255	0.7585
%Wt percentage of yttria(Y2O3)	-0.6507	0.1791	-0.3255	-0.0256	0.8236	-0.4335	0.7923
%Wt percentage of Alumina(Al2O3)	1.2352	-3.6385	0.8047	0.2488	2.7272	-1.0854	-0.2939
%Wt percentage of Calcia(CaO)	1.0862	-3.6535	-0.2909	0.1511	3.8253	-1.6611	-0.2833

Conclusions

A comprehensive integrated material selection approach has been developed according to the research results. It is based on the comprehensive application of FUZZY-ENTROPY and FUZZY-TOPSIS methods as optimization techniques for data preparation and regression analysis as a supervised machine learning method for data prediction. Particularly, analytical dependencies for evaluating the physical and mechanical properties of dental crown material have been obtained. The proposed approach has been analyzed qualitatively regarding the impact of phase composition elements and sintering temperatures on physical and mechanical properties. The quantitative criteria for proving the reliability of the proposed approach have also been calculated (i.e., mean average percentage error and root mean square error), and the following conclusions were extracted from the study.

1-3Y-PSZ(from TYPE1 to TYPE 5),4Y-PSZ(from TYPE6 to TYPE10),5Y-PSZ(from TYPE 11to TYPE15), and CSZ(from TYPE32 to TYPE 35) are promising bioceramic materials and have the best physical, mechanical and aesthetic properties according to the direct model.

2-Direct model and Inverse model will provide initial support for researchers to do experimental work on dental ceramics especially materials that are accepted by our model, and that will save money and cost.

3- A direct model will help researchers monitor the physical and mechanical properties of certain dental ceramics in case of feeding it with the composition of materials and that will help them reach faster to optimum dental materials suitable for manufacturing conditions and the demand of customers.

4- The inverse model will also help researchers to determine the scope of dental ceramic materials composition in case of feeding the model with physical, mechanical, and aesthetic properties suitable for manufacturing.

After using our model for dental crown materials design, it is proposed to use the prepared material for slurry-based ceramic printing not for powder-based ceramic printing to avoid thermal stresses on bioceramic prepared material, then after using slurry-based ceramic printing, it's advisable to put the following points in our consideration:

- The slurry-based ceramic materials should be homogenous by ball milling with a particle size of the range(0.2:0.5)micron
- The solid content of ceramic slurry should be greater than 40vol% to ensure minimum porosity and maximum flexural strength
- Viscosity of suspension shouldn't exceed 3 pa. sec as higher viscosities prevent the recoating of homogenous layers
- Additive manufacturing process parameters such as layer thickness, printing speed, laser power should be optimized to get an excellent quality for manufactured part
- A printed part should be characterized to ensure that it achieves the expected dimensional accuracy, surface quality, biocompatibility, mechanical properties, delivery time, and productivity.

Although our approach suffered from a lack of experimental work, it could be a promising initial step for researchers in bioceramics as a powerful decision making that could help them to prepare an excellent bioceramic powder material for additive manufacturing. Overall, the developed approach is helpful for dental manufacturers to optimize dental crown material.

Nomenclature

EWM	**Entropy Weight Method**	**TOPSIS**	**Technique for Order Preference by similarity to ideal solution**
$\bar{X}^T$	**Transpose of normalized feature matrix of phase composition and sintering temperature**	$\bar{\bar{Y}}$	**The unknown matrix of physical and mechanical properties**
$\bar{X}_{i,j}$	**Normalized feature matrix of phase composition and sintering temperature**	θ	**Weighted factors of machine learning model**
E_j	**The entropy value of the jth index**	$s_i{}^+$	**Distance between alternatives (samples) and the PIS**
$MAPE_j$	**Mean Average Percentage Error of j indicators**	$RMSE_K$	**Root Mean Square Error of K attributes**
$NRMSE_K$	**Normalized Root Mean Square**	$[\theta]$	**Matrix of weighted factors**

	Error of K attributes		
P_{ij}	standardized value of the ith sample in jth indicator	A_i	Alternative of ith sample
W_j	Weight of Jth indicators	C_i^*	The relative closeness of ith samples
$\hat{X}$	The predicted label matrix	$\hat{\hat{X}}$	Expected normalized values of material compositions and sintering temperature
x_{ij}	values of material compositions and sintering temperature	$\bar{Y}_{i,j}$	Normalized label matrix of physical and mechanical properties
y_{ij}	values of physical and mechanical properties	s_i^-	Distance between alternatives (samples) and the NIS
d	Number of attributes (material composition elements)	r_{ij}	Elements of normalized decision matrix
i	Counter of n samples(i=1:n)	V	weighted normalized decision matrix
j	Counter of m indicators(1:m)	V^+	The vector of positive ideal solution
k	Counter of d attributes(1:d)	V^-	The vector of negative ideal solution
m	Number of indicators(physical properties)	R	The normalized decision matrix
n	Number of samples	D	The evaluation matrix
NIS	Negative Ideal Solution	PIS	Positive Ideal Solution
CSZ	Calcia stabilized zirconia	3Y-PSZ	(3%mol yttria)partially stabilized zirconia
4Y-PSZ	4%mol yttria)partially stabilized zirconia	5Y-PSZ	(5%mol yttria)partially stabilized zirconia
YSZ	Yttria Stabilized Zirconia	m	Number of indicators
n	Number of samples		

Declarations

Ethics aApproval and consent to participate

This article does not contain any studies with human participants or animals performed by the authors.

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Authors' contributions

AO : Conceptualization, Methodology, Analysis, Investigation, Writing - Original Draft, Validation, Software, Editing.NF: Supervision, Project administration, Review.ME: Supervision, Project administration, Review.

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Conflict of interest

The corresponding authors state that there is no conflict of interest.

Competing interests

The authors declare that they have no competing interests.

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