STATISTICAL MODELS FOR CERAMIC TILE HIGH-TEMPERATURE PHYSICAL PROPERTY CHANGES FOR FIRE AND HEAT SAFETY

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ABSTRACT:

In general, the properties of density, heat conductivity, and specific heat capacity of any material change when the temperature changes. The variations may be slight for some materials, such as ceramic tiles, which are used as floor, wall, and roof coverings in building construction. Moreover, the properties may change more or less linearly with the temperature in small intervals, but linear behaviors are possible in larger intervals of temperature variation. Plotting the available data usually gives a better picture of the relationship between each of these properties and temperature. From a statistical point of view, the data is usually modeled using linear, quadratic, exponential, logarithmic, and logistic equations where the method of least squares is used to find the relevant parameters of the model. Once the parameters are found, confidence intervals, which provide reliability measures for the variation in each property with temperature, can be determined.

This study investigated ceramic tiles' density, specific heat capacity, and thermal conductivity changes in the temperature range 0 – 1000 °C. When linear models were fitted to the data, only specific heat capacity showed a significant positive relationship with temperature. Density and thermal conductivity were effectively constant in the temperature range of 0 – 1000 °C. This paper will show results of statistical modeling, compare and contrast artificial intelligence (AI) predictions by the Naser-TCNA group, and present opportunities for ceramic tile as thermal insulating materials for safer fire and heat applications.

1. INTRODUCTION:

1.1. CERAMIC TILE THERMAL BEHAVIOR

Construction materials are an essential component of fire prevention and spread. The recent fire incidents have gained national and international attention due to those materials' flammability and flame spread properties. Grenfield tower fire incident London, the UK in 2017 (McKee 2017), Interstate 85 bridge collapse in Atlanta, USA (NTSB 2017), and hundreds of thousands of fires in the US every year cause thousands of lost lives and billions of dollars of economic damages (USFA and FEMA 2017). It appears that this trend is increasing mainly because how our society is changing to keep up with modern and recent trends in the construction industry. One such change is that synthetic organic polymers (SOP) (i.e., plastics) are new construction materials due to their lower costs and functional properties at ambient temperatures. However, these SOPs perform poorly under elevated temperatures and, subsequently they ignite and act as additional fuels. Unlike traditional building materials such as ceramic tiles, concrete, and steel, we found SOPs are chemically unstable at high temperatures (>100 ^{0}C) and are physically fragile structural systems.

Ceramic tiles are the only one or perhaps one of a few non-combustible materials used in building and bridge constructions. They are mainly used as floor, wall, or roof covering materials in building structures and as thermal insulation, chemical inertness or oxidation, and corrosion resistance; hence, easily cleanable, decorative properties in on-road bridges, tunnels, and parking garages. This is because ceramic tiles typically do not change their physical properties, ignite, ~~or~~ spread fire, or emit toxic gases and smoke from ambient to 1000 °C temperatures. Therefore, it is considered one of the safest construction materials.

Ceramic tiles are a mixture of clay or kaolin, quartz, and feldspar fired to 1000-1300 °C. The clay fraction helps in providing plasticity and dry mechanical strength during processing, feldspar develops glassy phases at low temperatures and assist in the sintering process, and quart promotes thermal and dimensional stabilities. Chemically, ceramic tiles are composed of silica (61-65%), alumina (16-18%), calcium oxides (6-10%), iron oxides (1-4%), and others (Fiori et al. 1989). The mineralogical composition is quartz (26-33%), anorthite (14-32%), feldspar (8%), albite (3-5%), other minerals, and amorphous phase (9-34%) (Fiori et al. 1989)(Han et al. 2013).

Using modern computational techniques (i.e., artificial neural networks and evolutionary genetic algorithms), our works so far demonstrated that ceramic tiles are good insulating materials for high-temperature applications. Our preliminary laboratory-scale prototype testing using ceramic wall tiles insulated concrete blocks heated up to 800 ^{0}C showed that ceramics are heat-insulating materials.

Compared to control (uninsulated specimens), ceramic tile insulated specimens experienced lower temperature rise while maintaining complete integrity (i.e., no cracking and spalling) during its four hours of temperature ramping and the post-fire cooling stage. To understand ceramic tile's high-temperature properties, and better design future generation of ceramic insulators, it is vital to know thermal properties (e.g., heat capacity and thermal conductivity), and densities, in addition to resulting mechanical properties and bonding behavior at elevated temperatures. This paper investigates ceramic tiles' high-temperature behavior of its physical properties mainly density, specific heat capacity, and thermal conductivity, using statistical modeling. In contrast to AI model results, the simple and easily conceivable statistical models could be useful in communicating ceramic tile high-temperature behavior for greater fire and heat safety.

1.2. MATHEMATICAL AND STATISTICAL MODELING

A statistical analysis of the data can be carried out to determine the behavior of the properties of the ceramic tiles when the temperature changes. As the first step, the scatter plots of the data can be drawn to observe any existing pattern.

If a linear relationship is suggested by the scatter plots, it is common to start the process by fitting a simple linear regression model for each data set choosing the property as the response variable and the temperature as the predictor variable. Suppose such a model gives rise to an intercept-only model (i.e., a constant model) as a result of temperature being not significant at a given level of significance. In that case, the average of the response variable can be used as a point estimate for the property in question. Furthermore, a confidence interval can be constructed for the average value as an interval estimate at a suitable level of significance. If the temperature is significant at that level of significance, one can use the simple linear regression model to represent the given set of data.

Statistical analysis is a fundamental and simple yet powerful approach to investigate and explain the relationship among variables. From a theoretical perspective, to be valid as statistical models, they must fulfill specific underlying assumptions. Once a model is fitted to the data, there are numerous ways to investigate the validity of those assumptions. In a situation where a fitted model is not adequate, it is common to transform the data before proceeding with the formulation of a simple linear regression model. In our case, where the objective is to ascertain how each property varies over the temperature range of 0 – 1000 °C, a simple linear regression model is appropriate.

1.3. AI AND NEURAL NETWORKS, AND THEIR POWER-PREVIOUS WORKS

Artificial intelligence (AI), from the view of this paper, refers to artificial neural networks (ANN). ANNs are a multi-layered algorithm where each layer comprises of a number of neurons. The first layer, called the input layer, receives the input (or properties of materials). The first layer is also connected to middle or hidden layer(s). The hidden layer(s) has the ability to establish nonparametric relations through transformation functions. On the other side, the hidden layer(s) is also connected to the output layer.

AI and ANN have been recently used to examine properties of materials. For example, Behnood and Golafshani developed a series of models to examine concrete derivatives (traditional concrete, concrete with waste foundry sand, and high-performance concrete), and asphalt materials with notable success and have led to creating new and simple models that can predict the properties of concrete and asphalt materials (Behnood and Golafshani 2020)(Behnood and Mohammadi Golafshani 2021). In addition, Naser and Thavarajah (Naser and Thavarajah 2021) also used such tools to explore the properties of ceramics. The use of ANN continues to be a new area of research on the front of materials property at elevated temperatures.

2. METHODS:

For this study, ceramic tile density, specific heat capacity, and thermal conductivity with temperature from ambient to 1000 °C data was obtained from a collection of studies. Density data was obtained from previously published studies (Al-Shantir and Trník 2017; Duvarci et al. 2007; Jankula et al. 2015; Michot et al. 2008). Specific heat capacity data was obtained from (Evans et al. 2014; García R. et al. 2009; Zhang et al. 2011; Jia, Kim, and Kriven 2007; Michot et al. 2008; Lonergan, Fahrenholtz, and Hilmas 2014; Michot et al. 2008; Dong et al. 2012).

Thermal conductivity data was obtained from (Michot et al. 2008; Michot et al. 2008; Liu et al. 2016; Zhao et al. 2019; Shu et al. 2012). Published from 2010-2020. The data presented in those published studies were extracted and used for further statistical processing as described below.

A simple linear regression model has the form

$$Y = \beta_0 + \beta_1 X$$

where Y is the response variable, X is the predictor variable, and β_0 and β_1 are parameters. In our case, Y represents one of the properties – density, specific heat capacity or thermal conductivity – and X represents temperature.

The least square estimates of the parameters are given by

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2}$$

and

$$\hat{\beta}_0 = \bar{Y} - \alpha\bar{X}.$$

A two-sided $100(1-\alpha)$ confidence interval for β_1 is given by

$$\hat{\beta}_1 \pm \frac{\sqrt{\frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}\right)^2}{n-2}}}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}}$$

If this interval does not contain 0, then the parameter β_1 is significant. If the interval contains 0, then the simple linear regression model reduces to the constant model

$$Y = \beta_0$$

and the least square estimate for β_0 is given by

$$\hat{\beta}_0 = \bar{Y}.$$

The plausibility of assumptions in a simple linear regression model and its adequacy are tested using the normal probability plot of residuals versus the predicted values, the Q-Q plot, and the residuals' histogram. The statistical analysis is carried out by using RStudio (Version 1.4.1106).

3. RESULTS AND DISCUSSION

The scatter diagram of each of the properties of density, specific heat capacity, and the thermal conductivity in the temperature range 0-1000 °C gives an idea about the behavior of each property with respect to temperature. The scatter diagrams of thermal conductivity data and the specific heat capacity data do not readily show any linear relationship rather than a somewhat random behavior. Still, the density data does suggest an apparent linear relationship (Figure 1). The fluctuations in the scatter diagrams could be expected due to several reasons. While the data we used are from various laboratories in various parts of the world, the tiles may have been made from different raw materials with different compositions. Also, various manufacturing processes would have included heating at a pre-specified maximum temperature and then cooling at a pre-specified rate to various physical properties. Moreover, different testing instruments and techniques may give rise to fluctuated readings, especially because of the sensitivity of the instruments to higher temperatures.

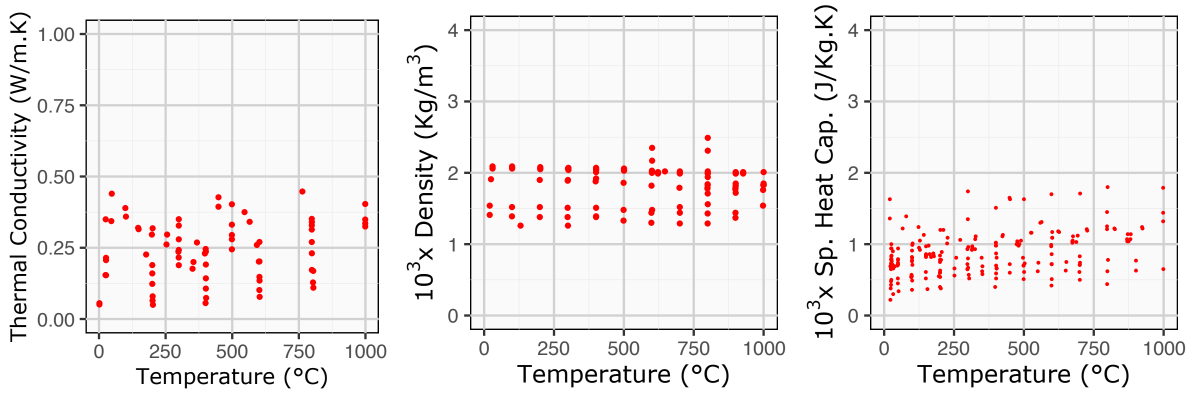

Figure 1: *Scatter diagrams of ceramic tile thermal conductivity, density, and specific heat capacity changes with temperature*

As an initial approach, a simple linear regression model was fitted for each property (response variable) by considering temperature as the predictor variable, and the results are given below.

For thermal conductivity, the model parameters were estimated to be

$$\beta_0 = 0.2121 \text{ and } \beta_1 = 0.00007142.$$

The adequacy of the model was tested with the residual plot, Q-Q plot and the residual's histogram (Figure 2). The three graphs perceptibly support the assumptions that are required for a simple linear regression model.

The p-value that corresponds to the significance of the predictor variable is 0.11, so the model reduces to the constant model (at the level of significance $\alpha = 0.05$) and hence an estimate for the thermal conductivity in the temperature range 0-1000 °C is given by the average of the predictor variables, viz.,

$$\text{Thermal Conductivity} = 0.2425\ \text{W/mK}.$$

The 95% confidence interval for thermal conductivity is given by (0.2100, 0.2750).

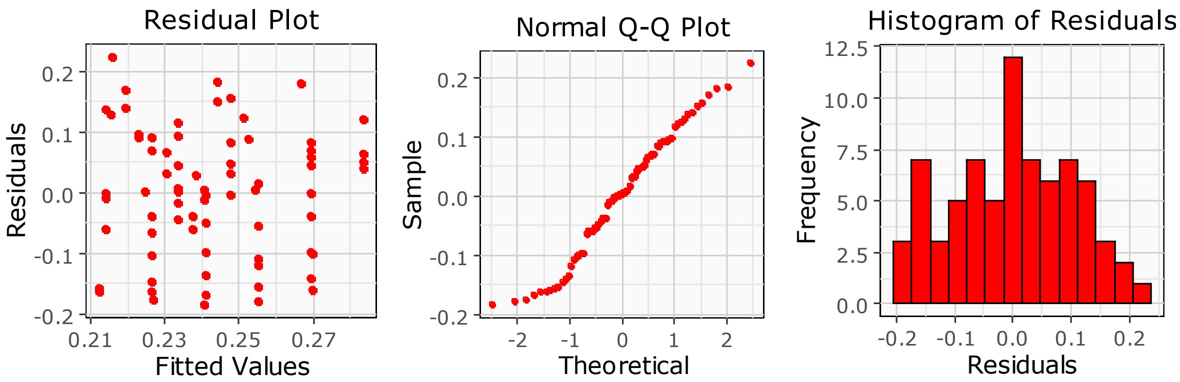

Figure 2*: Residual Plot, Q-Q Plot and the Histogram of Residuals for Thermal Conductivity Data*

For density, the model parameters were estimated to be

$$\beta_0 = 1797 \text{ and } \beta_1 = 0.04092.$$

The adequacy of the model was tested with the residual plot, Q-Q plot and the residual's histogram (Figure 3). Though the plots are not as desirable as those for the thermal conductivity, there are no serious violations of the assumptions.

The p-value that corresponds to the significance of the predictor variable is 0.668, so that the model reduces to the constant model and hence an estimate for the density in the temperature range 0-1000 °C is given by the average of the predictor variables, viz.,

$$\text{Density} = 1820\ \text{Kg/m}^3.$$

The 95% confidence interval for density is given by (1745, 1894).

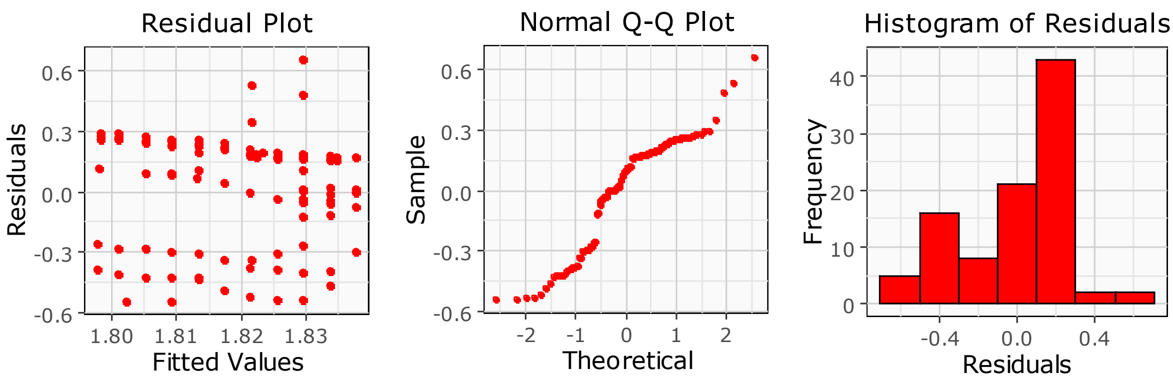

Figure 3: *Residual Plot, Q-Q Plot and the Histogram of Residuals for Density Data*

Finally, for specific heat capacity, the model parameters were estimated to be

$$\beta_0 = 722 \text{ and } \beta_1 = 0.40441.$$

The adequacy of the model was tested with the residual plot, Q-Q plot and the residual's histogram (Figure 4). The plots are not as desirable as those for the thermal conductivity, but look better than those for the density data, and again there are no serious violations of the assumptions.

The *p*-value that corresponds to the significance of the predictor variable is very small ($= 3.81 \times 10^{-8}$), so that the temperature is significant at 5% level of confidence. Therefore, we stay with the simple linear regression model,

$$\text{Specific Heat Capacity} = 722 + 0.40441 \times \text{Temperature}$$

in the temperature range 0 – 1000 °C.

The band of confidence intervals for the mean predicted values calculated from the fitted model is given in Figure 5.

The specific heat capacity data was transformed using a log function to see whether there is an improvement in the simple linear regression model, but no significant improvement was visible.

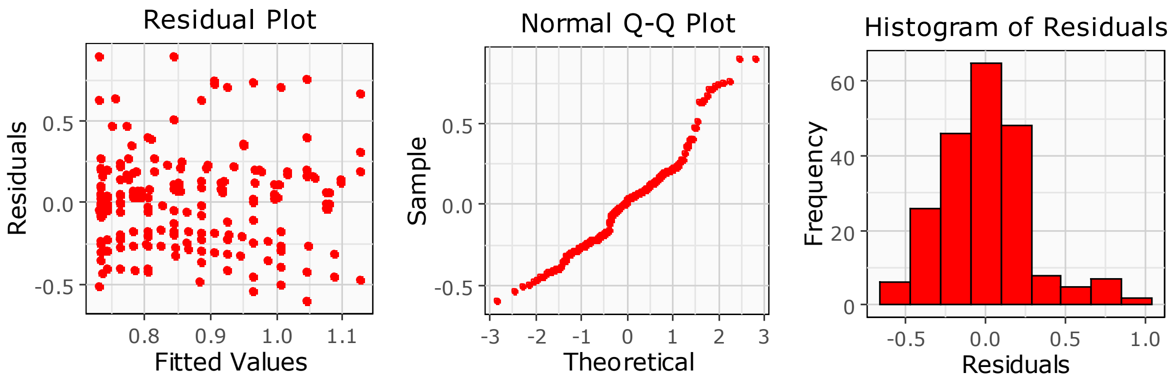

Figure 4: *Residual Plot, Q-Q Plot and the Histogram of Residuals for Specific Heat Capacity Data*

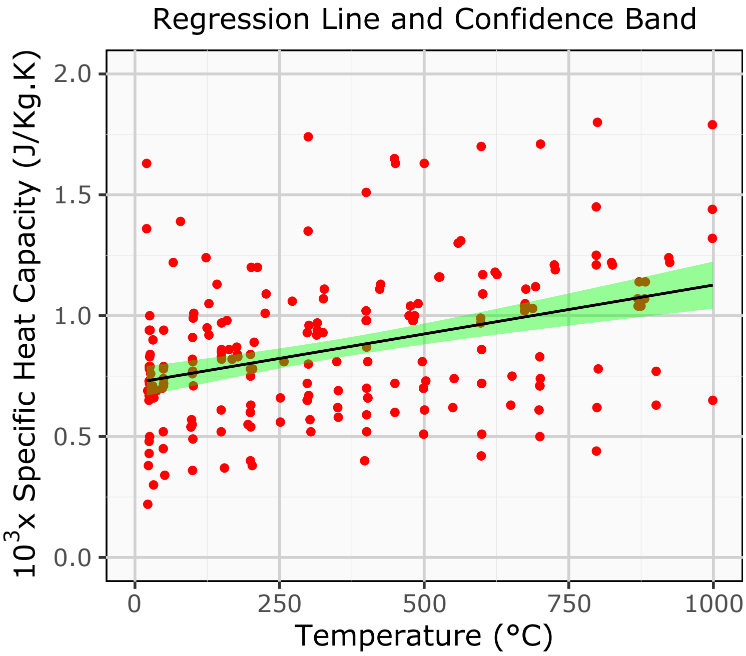

Figure 5: *Regression line and the confidence band for the mean predicted values for specific heat capacity data*

Finally, this statistical modelling results were compared with previously published ANN results by Naser and Thavarajah (Behnood and Mohammadi Golafshani 2021). Those two different methods physical property data from 0-1000 ºC are presented in Table 1. The density data are comparable between the two methods. However, thermal conductivity was lower when using statistical modelling than that of ANN. Although heat capacity data are comparable between each method, an increasing heat capacity trend was observed in statistical model whereas ANN did not show a linear increasing trend.

Property	ANN (Naser & Thavarajah, 2021)	Statistical Modelling
Density (kg/m^3)	1793-2158	1745-1894
Thermal Conductivity (W/m.K)	0.52-2.00	0.21-0.27
Specific heat capacity (J/Kg.K)	571-1328	722-1126

Table 1: *Comparison of physical property data from statistical modelling and ANN.*

4. CONCLUSIONS

The variations of the three properties – thermal conductivity, density, and the specific heat capacity - in the temperature range 0 - 1000 °C can be modeled using basic statistical tools. If follows that the thermal conductivity and the density of the tiles remain constant. Specifically, the average value of the thermal conductivity is 0.2425 W/m.K and, based on the data used, there is a 95% confidence that this value is between 0.2100 and 0.2750. Similarly, the average value of the density is $1820\ Kg/m^3$ and there is a 95% confidence interval that this value is between 1745 and 1894. In contrast, the temperature affects the specific heat capacity significantly and the relationship between the specific heat capacity and the temperature is given by the following linear model.

$$\text{Specific Heat Capacity} = 722 + 0.40441 \times \text{Temperature}$$

Based on the analysis of this work, the key conclusions arrived at via this investigation infer that it seems that ANN can capture the variation of material properties at elevated temperature in a more robust manner than statistical methods. However, the choice of the method to use could be dependent upon the upper tolerance values for each temperature range to provide the greater fire and heat safety.

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