

# Research on Optimal Fabrication of High-Quality Ceramic by Process Analysis Technology <sup>†</sup>

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**Abstract:** We developed a composite recognition method combining hybrid sensor recognition and artificial intelligence image recognition techniques and optimized quality monitoring of the ceramic production process. By integrating deep learning models and image preprocessing techniques, appearance defects (such as cracks and color differences) were detected in ceramic products, and key parameters in the sintering process using temperature, pressure, and gas-sensitive sensors were monitored in real-time. The developed composite recognition method significantly improved the quality control level of ceramic production, reduced production energy consumption and wastes, and improved production efficiency.

**Keywords:** laser-induced breakdown spectroscopy (LIBS); artificial intelligence recognition; ceramic production; quality optimization

## 1. Introduction

In ceramic production, traditional quality monitoring methods are inefficient and inaccurate. To solve this problem, we introduced laser-induced breakdown spectroscopy (LIBS) technology and combined it with artificial intelligence (AI) image recognition technology [1]. A deep learning model was constructed to detect the appearance defects of ceramic products in real-time and improve the detection accuracy. Temperature, pressure, and gas-sensitive sensors were introduced to monitor key parameters in the sintering process in real-time. Based on the data, a new and efficient quality monitoring solution was developed for ceramic production [2].

## 2. Methods

### 2.1. Process Analytical Techniques

Process Analytical Technology (PAT) is an advanced manufacturing technology used in the pharmaceutical, chemical, and food industries. PAT is issued for designing, analyzing, and controlling the production by real-time monitoring of the quality and performance of raw materials, intermediates, and processes [1]. The technology ensures the high quality of the final product while increasing productivity and reducing costs. The PAT technology reduces the uncertainty in the production process and improves the controllability of the process, leading to a stable and predictable production process. It consists of online, at-line, and in-line analytical methods that monitor Critical Quality Attributes (CQAs) and Critical Process Parameters (CPPs) in the production process.



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## 2.2. LIBS

LIBS is an atomic spectroscopy technique for elemental analysis using high-power laser pulses focused on the surface of a sample, ablating the sample, and forming a short-lived, high-temperature plasma [2]. The LIBS technique allows for the rapid and portable measurement of major and trace element concentrations in solid, liquid, or gaseous samples to record a material's chemical signature (fingerprinting). Each LIBS spectrum contains information about the concentrations of all naturally occurring elements, isotopic ratios, and information on the atomic structure of the material. LIBS ablates atoms from the surface of the sample to form a high-temperature plasma using high-power laser pulses as the energy source. The plasma temperature is high above 10,000 K and has enough energy to excite electrons in outer orbitals. As the plasma cools, the excited electrons decay to lower energy orbitals, emitting photons that are inversely proportional to the energy difference between the excited and base orbitals. Each element has multiple emission wavelengths due to the existence of multiple possible excited states.

## 2.3. Partial Least Squares Regression

Partial Least Squares Regression (PLS) is used to model the relationship between multiple independent and dependent variables, especially in the presence of multicollinearity. PLS combines the ideas of Principal Component Analysis (PCA) and Typical Correlation Analysis (CCA) by extracting independent and dependent variables to establish a linear relationship between them. These main components are called PLS components or factors, which present linear combinations of the original variables and maximum covariance with the dependent variable. The goal of PLS is to find a new set of variables (PLS components) that are linear to the original independent variables and have maximum correlation with the dependent variable.

To extract PLS components, the first set of PLS components, which reflect both the trend of the independent variable and the trend of the dependent variable, are extracted by an iterative algorithm (e.g., the NIPALS algorithm). Specifically, PLS looks for linear combinations of  $X$  and  $Y$  that maximize their covariance (1).

$$\max \text{Cov}(X_p, Y_q) = \sqrt{\text{Var}(X_p)\text{Var}(Y_q)}R(X_p, Y_q) \quad (1)$$

## 3. Model Construction

### 3.1. Regression Modeling

In the analysis of the chemical composition of ceramic materials based on LIBS, PLS is an effective statistical method for establishing a linear relationship between the LIBS spectral data (independent variable) and the chemical composition of the ceramic material (dependent variable). PLS is used to construct a prediction model by extracting the common variance information between the two sets of data, thus realizing the accurate prediction of chemical composition [3,4]. In the basic form of a PLS model, the chemical composition is predicted by establishing a linear relationship between the independent variable (LIBS spectral data,  $X$ ) and the dependent variable (chemical composition of the ceramic material,  $Y$ ). The model is expressed as (2).

$$Y = XB + E \quad (2)$$

where  $Y$  represents the dependent variable, i.e., the chemical composition of the ceramic material,  $X$  represents the independent variable, i.e., LIBS spectral data,  $B$  represents the matrix of regression coefficients for the PLS model, and  $E$  represents the error term, indicating the portion of variation in  $Y$  that the model fails to explain.

The core of the PLS model is to find the optimal projection between X and Y. In this study, we used the score vector (T) and the load vector (P) to establish a linear relationship between them by using (3).

$$\begin{aligned} X &\approx TPT^T + E \\ Y &\approx TTC + F \end{aligned} \quad (3)$$

where T is the score matrix that contains a projection of the X and Y co-variance information, P is the loading matrix representing the coefficients of X in the score space, r is the number of components selected, i.e., PLS components retained,  $t_i$  and  $p_i$  are the  $i$ th score vector and load vector, respectively, E is the residual matrix of X, indicating the fraction of the score space that is not explained by the model, and C and F are the coefficients of the score matrix and load matrix of Y, respectively, which are used to describe the structure of Y in the score space.

In this way, the PLS model effectively extracts key information related to chemical composition from high-dimensional LIBS spectral data, and then accurately predicts the chemical composition of ceramic materials [5]. Specifically, the modeling is screened by a computer (Figure 1).

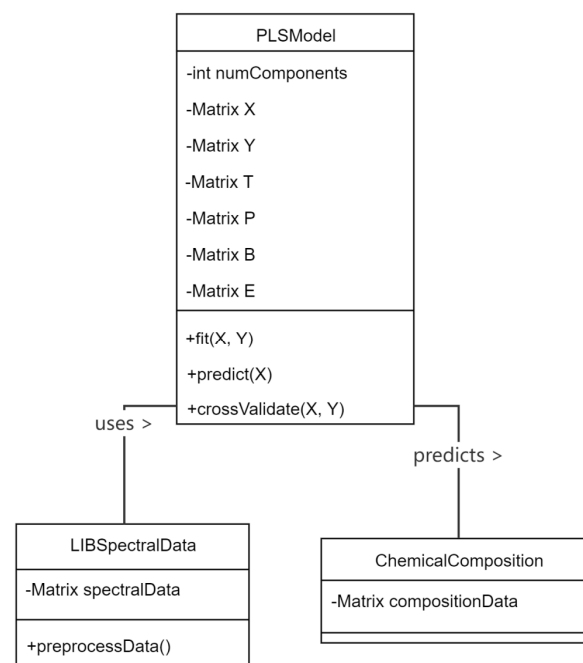


**Figure 1.** Computer modeling class diagram for constructing regression models underlying process analysis in ceramic production.

Within the framework of PLS, the selection of an appropriate number of components (r) is crucial for the construction of the model, which usually relies on the cross-validation technique. The number is used to evaluate the predictive efficacy of the model and effectively avoid the overfitting phenomenon to ensure the accuracy of the model prediction. Optimization and validation of the model are important for guaranteeing the predictive accuracy and reliability of the PLS model [6]. The process of model optimization and validation is of great significance in ensuring the accuracy and reliability of PLS models [6].

### 3.2. Data Fusion and PAT in Ceramics Production

The application of PAT is crucial in the study of optimization of high-quality ceramic production, and multiple data source correction plays an important role. In this study, data from different sensors, such as thermometers, manometers, flow meters, and spectral

analyzers, were integrated to improve the accuracy and consistency of the data. The purpose of the integration of multiple data sources is to ensure that data collected from different sensors provide comprehensive and accurate information about the production process. This involves data preprocessing, feature extraction, data fusion, and result validation. In preprocessing, the data need to be filtered, denoised, and normalized [7]. Feature extraction, on the other hand, extracts key information from the raw data that has an impact on the production process. Data fusion is the process of integrating data from different sensors to form a comprehensive and consistent dataset, and result validation is an important step to ensure that the corrected data meet the production requirements.

In ceramic production, dry-press molding technology significantly improves the production efficiency of silicon carbide ceramic micro-airborne disks while maintaining high product consistency. By optimizing the dry-press molding process, the dimensional accuracy of SiC micro-empty discs is significantly improved to meet the application requirements of precision devices. The sintered SiC micro-empty discs show excellent mechanical properties, including high flexural strength and wear resistance. The application of PAT is not limited to the analysis of single-sensor data, but through the integration of a wide range of sensor data, such as temperature and pressure, the production process is monitored. These technologies are used to analyze key quality attributes of ceramic materials such as chemical composition, crystal shape, and particle size distribution. By using PCA and PLS, invalid information is effectively filtered out and the problem of covariance is solved for complex analysis [3,7]. The multi-data source correction technique plays a crucial role in PAT-based optimization studies of high-quality ceramic production as it provides an accurate view of the production process by integrating and correcting data from different sensors, thus helping manufacturers optimize the production process, improve product quality, reduce costs, and ultimately achieve automated and intelligent production [8] (Figure 2).

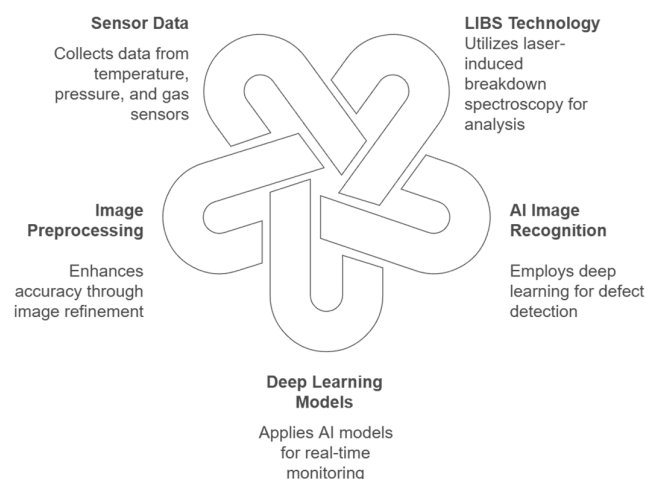


**Figure 2.** Schematic framework of the application of the data fusion language PAT in ceramic production.

### 3.3. Optimization of AI in Process Analysis

PAT plays a vital role in the optimization of high-quality ceramic production. The core of PAT lies in the real-time monitoring and control of CQAs and CPPs in the production process and ensuring the consistency and quality of the final product. In ceramic production, this involves precise control of all aspects of raw material proportioning, molding, drying, and sintering [9]. CQAs and CPPs are important in ceramic products and real-time monitoring of these parameters allows timely adjustment of the production process to ensure consistency and predictability of product quality. In ceramic production, sintering

temperature and time are the key parameters for ceramic strength and density, while the strength of ceramics is a key quality measure. With PAT technology, the temperature and time can be monitored in real-time in the sintering process to ensure that the ceramic products produced meet the required strength criteria [10] (Table 1).

**Table 1.** Indicators for optimizing CQAs and CPPs for high-quality ceramic production.

|      |                                          |                                  |
|------|------------------------------------------|----------------------------------|
| CQAs | Key attributes affecting product quality | Compressive strength of ceramics |
|      |                                          | Surface finish                   |
|      |                                          | Dimensional accuracy             |
|      |                                          | Color uniformity                 |
| CPPs | Process parameters affecting CQAs        | Sintering temperature            |
|      |                                          | Sintering time                   |
|      |                                          | Raw material mixing uniformity   |
|      |                                          | Drying rate                      |

AI image recognition technology in the optimization of ceramic production is used to analyze image data for automated quality inspection and defect identification. Through deep learning algorithms such as convolutional neural networks (CNNs), features are automatically extracted from image data to identify defects such as cracks, bubbles, and color differences on the surface of the product. Then, real-time monitoring and quality control of the production process are achieved. LIBS is a fast and non-destructive detection means for the chemical composition analysis of ceramic materials. LIBS technology provides the chemical composition of materials in real-time by analyzing the plasma emission spectra formed on the surface of the samples after they are ablated by high-energy laser pulses. Combined with statistical methods such as Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), the ceramic fragments are quickly identified. By integrating data from different sensors, such as LIBS, machine vision, weight monitoring, and acoustic wave detection, the production process is monitored and the accuracy, and reliability of the data analysis are improved. This multi-sensor fusion approach provides information to optimize the production process and improve product quality and productivity.

## 4. LIBS and PLS

### 4.1. Simulation

Numerical simulation was conducted to investigate the propagation characteristics of high-power laser pulses in ceramic materials by constructing a mathematical model. We analyzed the kinetic process of the interaction of laser pulses with ceramic materials and the spatial and temporal distributions of the laser energy inside the materials [11]. A series of key laser parameters was defined as follows.

|                                                                                                                                                                                                                                                                                                                                                                 |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Wavelength ( $\lambda = 1064 \times 10^{-9}$ meters)<br>Transmission distance ( $L = 1 \times 10^{-3}$ meters)<br>Time step ( $dt = 1 \times 10^{-14}$ seconds)<br>Beam radius of the laser beam ( $w_0 = 1 \times 10^{-3}$ meters)<br>Amplitude of the laser pulse ( $A = 1$ )<br>pulse width ( $\tau = 50 \times dt$ )<br>peak time ( $t_0 = 200 \times dt$ ) |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|

These parameters presented the spatiotemporal characteristics of the laser pulse for subsequent numerical simulations. In this study, a mathematical model based on Gaussian

distribution was simulated to describe the spatiotemporal distribution of the laser pulse. The Gaussian distribution of the laser pulse in the time dimension and the attenuation characteristics along the transmission distance were simulated by using this model. A three-dimensional grid was created using the meshgrid function in MATLAB R2021b software, which covers the entire spatial and temporal range of the simulation, and the distribution of the electric field intensity was visualized using three-dimensional mapping techniques [12] (Figure 3).

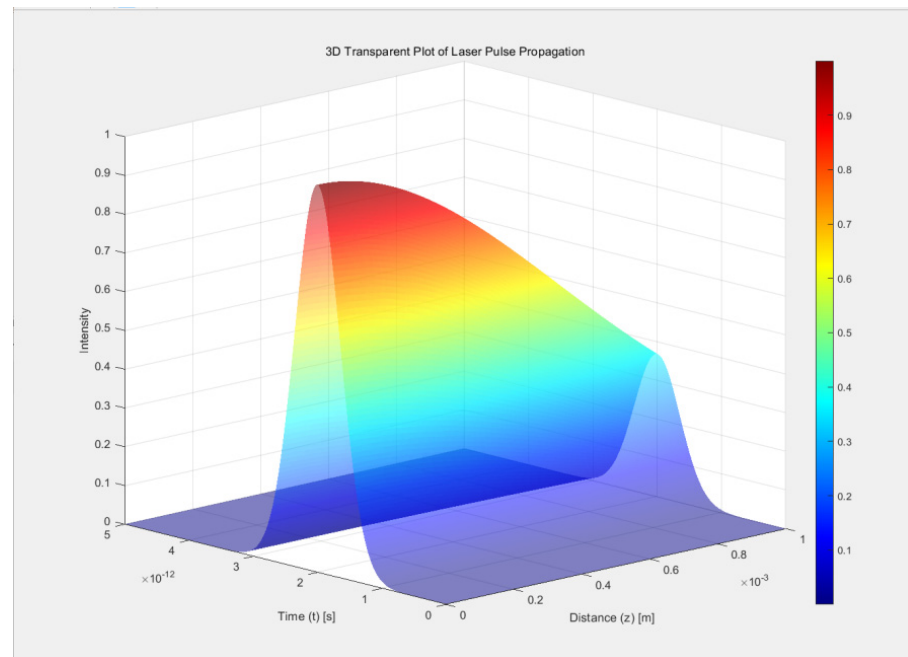


**Figure 3.** Experimental simulation of propagation characteristics of high-power laser pulses in ceramic materials.

#### 4.2. PLS

PLS analysis was performed to establish a linear relationship between LIBS data and the chemical composition of ceramic materials. In the LIBS analysis, the spectral data (usually denoted as  $V_1, V_2, \dots, V_n$ ) represent the emission intensity of a ceramic material at a specific wavelength. There is a complex nonlinear relationship between these spectral data and the chemical composition of the ceramic material. The linear relationship between these spectral data and the chemical composition was established by using a PLS model to understand and predict the chemical properties of the materials. The LIBS spectral data and the chemical composition data were normalized to eliminate the effect of different magnitudes and used to model using the `pls` function. The PLS model was established by the leave-one-out (LOO) method. Cross-validation of the different numbers of principal components was carried out to assess their effect on the prediction performance. The results of the experiment are shown in Table 2.

Comp 1 is positively correlated with  $V_4$  and  $V_8$  and negatively correlated with  $V_3$ . Spectral data for  $V_4$  and  $V_8$  are important in characterizing certain chemical components, while  $V_3$  may be negatively correlated with these chemical components. Comp 2 is positively correlated with  $V_5$  and negatively correlated with  $V_3$  and  $V_6$ .  $V_5$  represents the emission characteristics of a specific element in the ceramic material, while  $V_3$  and  $V_6$  are negatively correlated with the content of that element. Comp 3 is positively correlated with  $V_1$  and  $V_9$  and negatively correlated with  $V_6$ .  $V_1$  and  $V_9$  are more critical in describing certain chemical properties of ceramic materials, while  $V_6$  is negatively correlated with these properties.

**Table 2.** PLS analysis results.

|     | Comp 1       | Comp 2       | Comp 3       |
|-----|--------------|--------------|--------------|
| V1  | 0.225805958  | −0.252367019 | 0.551012434  |
| V2  | −0.086603498 | 0.081155404  | 0.329024037  |
| V3  | −0.393079975 | −0.279781825 | −0.047168851 |
| V4  | 0.55781294   | −0.194465185 | −0.221014594 |
| V5  | −0.012045793 | 0.711815864  | −0.208958142 |
| V6  | −0.129256317 | 0.237695426  | −0.517497336 |
| V7  | 0.154309764  | 0.485083531  | 0.202877961  |
| V8  | 0.417147893  | −0.207197416 | 0.125774642  |
| V9  | −0.262474818 | 0.108665398  | 0.515956505  |
| V10 | 0.462480944  | −0.011035023 | −0.019325213 |

The experimental results showed that the PLS model performed well in explaining the variance of the LIBS spectral data. The model's ability to explain the variance of the independent variable (LIBS spectral data) improved with the increase in the number of principal components, from 13.62 to 34.12% on the training set. For the dependent variable (chemical composition), the model's variance explaining ability increased from 10.42 to 10.72%.

## 5. Conclusions

We developed and validated a composite recognition model based on LIBS and AI image recognition techniques for monitoring the quality of ceramic products. The appearance defects of ceramic products were detected in real-time, and the key parameters during the sintering process were monitored, which significantly improved the quality control of ceramic production. By reducing energy consumption and waste in production, production efficiency increased and production costs were reduced. Further composite recognition research is required for other industrial productions, promoting the intelligent and automated production process.

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