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MODELLING AND SIMULATING THE PRESSING PROCESS OF IRON POWDERS WITH DIFFERENT PARTICLE SIZES

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Abstract. This paper brings into focus new modelling features in the context of pressing process of iron powders with different particle sizes. The study is focused on the evolution of green density function of the pressing speed, pressure and iron particle size and it's important in the elaboration of sintered steels by gas-carbu-sintering process in powder metallurgy. The significance of the work consists in the new interdisciplinary approach realized by matching the experiments with the mathematical model and the computational simulations. The statistical information and data are important in further analysis and experiments.

Keywords: iron powders, pressing speed, interactive modelling, statistical data mining

1. Introduction

1.1. Recent trends in Powder Metallurgy

Powder Metallurgy (PM) is one of the technologies which respond at two main conditions: save materials and save energy. To obtain PM parts is necessary to follow some important steps such as: mixing, forming, sintering and sizing. Depending on the shape and properties to be achieved there are several additional operations as following: de-burring, machining, oil or resin impregnation, plating, heat treatments and so on. The forming process consists in different technologies and the main of them is die compaction [1]. Depends on the shape complexity there are different ways to obtain green parts from unilateral pressing with simple and double action until cold or hot isostatic pressing [2, 3]. The die compaction it's the most important step to obtain green compacts with uniform density, near net shape, without internal cracks and also allows minimizing or eliminating the finishing operations [4].

This study is focused on the modeling and simulation the evolution of green density function the pressing speed, pressure and iron particle size which is important in the elaboration of sintered steels by gas-carbu-sintering process [5, 6].

1.2. The mathematical-statistical context of data mining

Data mining is an analytic process designed to explore large amounts of data (typically business or market related) in search of consistent patterns and/or systematic relationships between variables, and then to validate the findings by applying the detected patterns to new subsets of data. The ultimate goal of data mining is prediction; predictive data mining is the most common type of data mining and has the most direct industrial and business applications [7].

The process consists of three basic stages:

1. Initial exploration
2. Model building or pattern identification with validation/verification, and concluded with
3. Deployment (i.e., the application of the model to new data in order to generate predictions).

Stage 1: Exploration. This stage usually starts with data preparation that may involve cleaning data, data transformations, selecting subsets of records, and, in case of data sets with large numbers of variables ("fields"), performing some preliminary feature selection operations to bring the number of variables to a manageable range (depending on the statistical methods being considered) [8]. Then, depending on the nature of the analytic problem, this first stage of the process of data mining can involve anywhere from a simple choice of straightforward predictors for a regression model, to elaborate exploratory analyses using a wide variety of graphical and statistical methods in order to identify the most relevant variables and determine the complexity and/or the general nature of models that can be taken into account in the next stage.

Stage 2: Model building and validation. This stage involves considering various models and choosing the best one based on their predictive performance (i.e., explaining the variability in question and producing stable results across samples). This may sound like a simple operation, but in fact, it sometimes involves a very elaborate process. There are a variety of techniques developed to achieve this goal, many of which are based on so-called "competitive evaluation of models," that is, applying different models to the same data set and then comparing their performance to choose the best.

Stage 3: Deployment. This final stage involves using the model selected as best in the previous stage and applying it to new data in order to generate predictions or estimates of the expected outcome.

The concept of data mining is becoming increasingly popular as a business information management tool where it is expected to reveal knowledge structures that can guide decisions in conditions of limited certainty. Recently, there has been increased interest in developing new analytic techniques specifically designed to address the issues relevant to industrial and business data mining.

However, an important general difference in the focus and purpose between data mining and the traditional Exploratory Data Analysis (EDA) is that data mining is more oriented toward applications than the basic nature of the underlying phenomena. In other words, data mining is relatively less concerned with identifying the specific relations between the involved variables. For example, uncovering the nature of the underlying functions or the specific types of interactive, multivariate dependencies between variables are not the main goal of data mining.

Instead, the focus is on producing a solution that can generate useful predictions. Therefore, data mining accepts, among others, a "black box" approach to data exploration or knowledge discovery and uses not only the traditional exploratory data analysis techniques, but also such techniques as *Neural Networks*, which can generate valid predictions but are not capable of identifying the specific nature of the interrelations between the variables on which the predictions are based.

2. Experiments and simulations for the pressing process

2.1. Recent experiments and data used

There were made experimental research regarding the influence of pressing speed on the density respectively porosity of iron powders with different particle size. For the experimental work were used iron powders from Ductil SA Buzau with different particles sizes (56 μm, 100 μm and 200 μm). The powders properties are presented in tables 1 and 2.

Table 1. Chemical properties of Fe powder

CHEMICAL ELEMENT	MAX [%]
Carbon, C%	0,02
Sulfur, S%	0,015
Phosphorus, P%	0,02
Silicon, Si%	0,05
Manganese, Mn%	0,20
Oxygen, O%	0,22

Table 2 Physical properties of Fe powder

PROPERTY	MIN	MAX
Hall Apparent Density [g/cm^3]	2,50	2,70
Hall Flow Rate [sec/50g]	31	33

The green compacts were obtained using a cylindrical die at three pressures: 200, 300 respectively 400 MPa and five pressing speeds: 10, 20 up to 50 mm/min.

2.2. The mathematical modelling and computational simulation of the process

In the first stage, it was realized the statistical model associated to the experimental research described above. In this order, there were used a lot of 27 data from a greater one of 45 collected from the experiment. The data were divided intro three cases, following three powder particle size cases: 56 μm, 100 μm and 200 μm. In each case, three density values were taken for each pressing force case: 200MPa, 300 and 400MPa, according with three values for the pressing velocity (10 mm/min, 20 and 50 mm/min). The surfaces were realized in STATISTICA soft, both for a linear and quadratic case. This two cases taken into account give rise to deduce some analytical behaviour for the expression $\rho = \rho(Force,\ velocity)$ of density variation with respect to the other variables.

Below there, figures 1 ÷ 6, are the graphs of the six surfaces.

In the second stage, the models obtained in STATISTICA soft were tested. The analytical expressions obtained for all cases (linear and quadratic) were tested with few values for the density, in order to realize multiple plots for verifying if the empiric values fit with the experimental ones. This would validate the computational work. It was used a new and fast interactive tool of MAPLE11 soft, namely *InteractiveDataAnalysis*. This appliance allows the simultaneous study of two or more data sets, by organizing them in vectors. The basic statistic indicators for the data sets are also calculated. Finally, the user has to choose from a lot of some important plots.

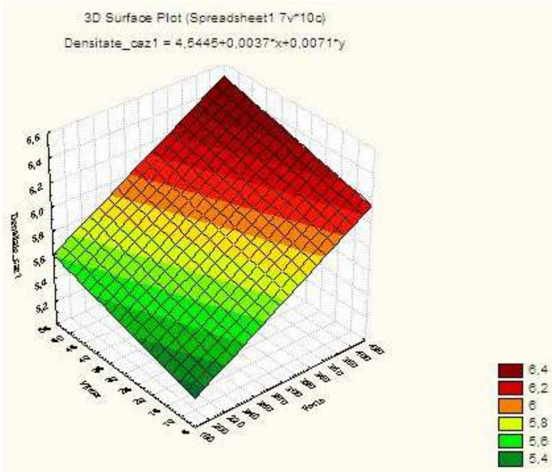

Figure 1. Case1-linear surface for 56µm particle size

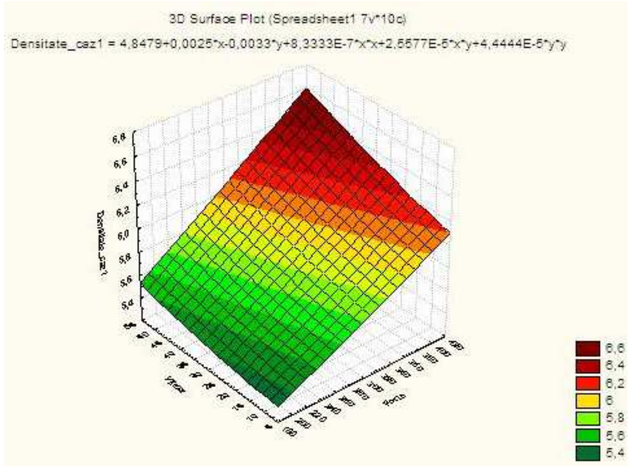

Figure 2. Case1-quadratic surface for 56µm particle size

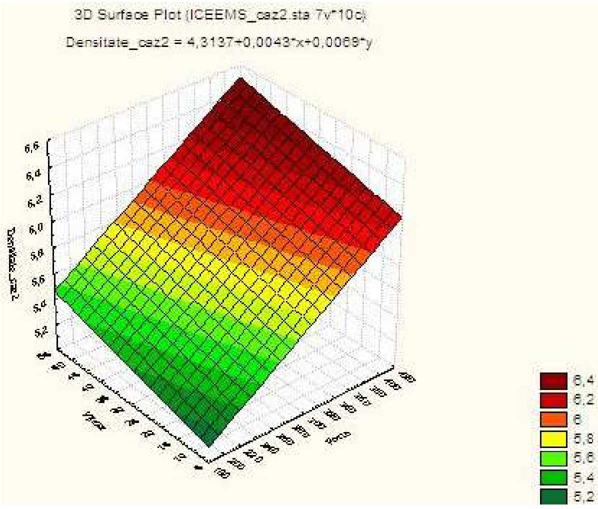

Figure 3. Case2-linear surface for 100 µm particle size

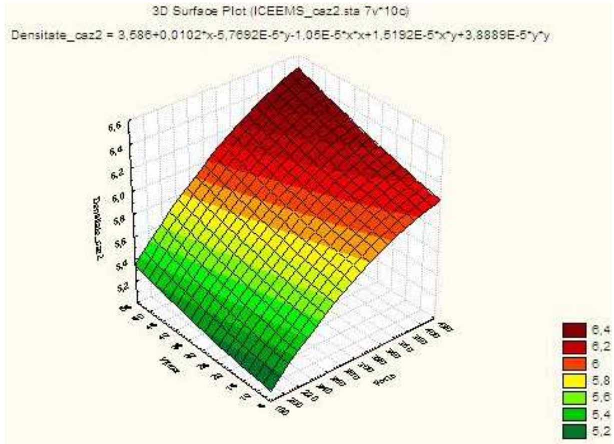

Figure 4. Case2-quadratic surface for 100 µm particle size

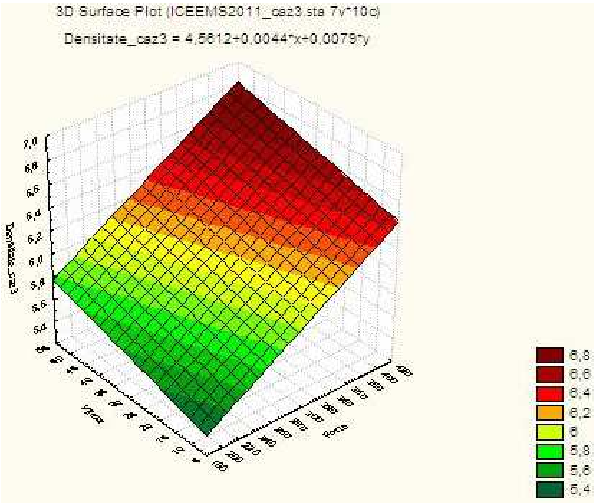

Figure 5. Case3-linear surface for 200 µm particle size

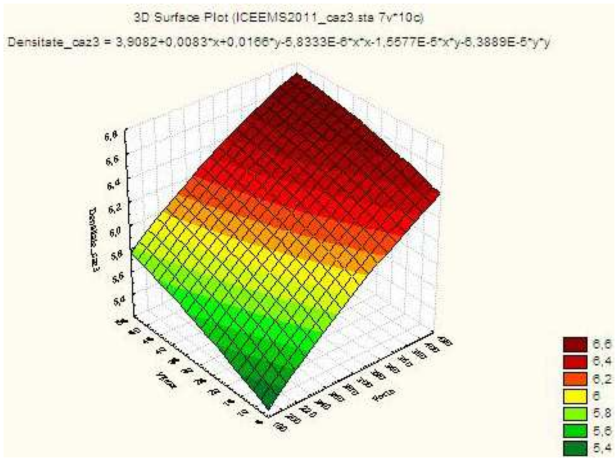

Figure 6. Case3-quadratic surface for 200 µm particle size

For the present aim, we have to analyse the variation of the density – the empirical values versus the experimental values. This variation is tested for the same *three powder particle size cases*: 56 µm, 100 µm and 200 µm. It was chosen a plot of normal type, and it was realized with respect to the experimental data. Since the plots feature is the same for the linear and quadratic case, it is presented only the linear case. Below, figures 7, 8 and 9, follow the comparative plots for the three cases.

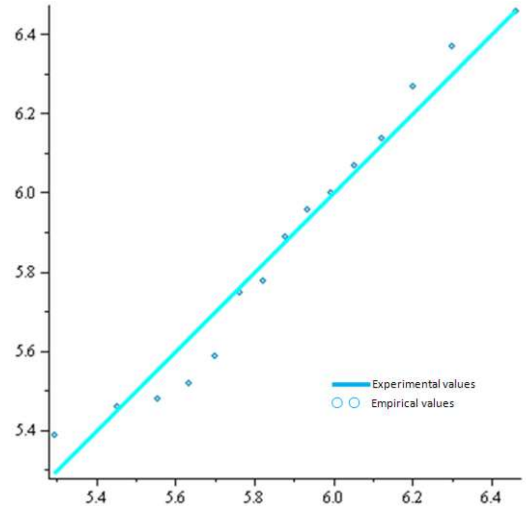

Figure 7. Comparative normal plot for the case1_linear

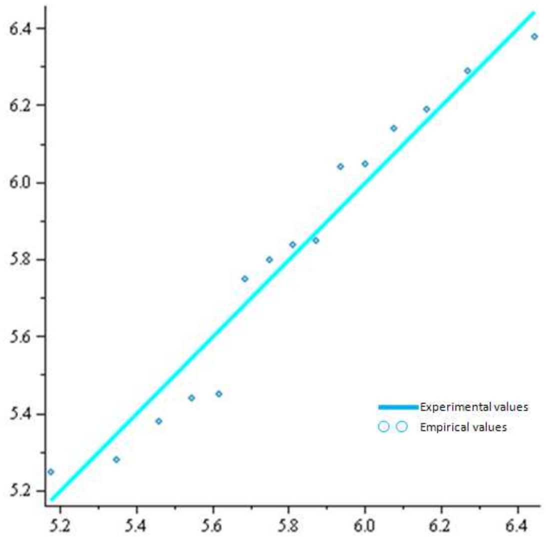

Figure 8. Comparative normal plot for the case 2_linear

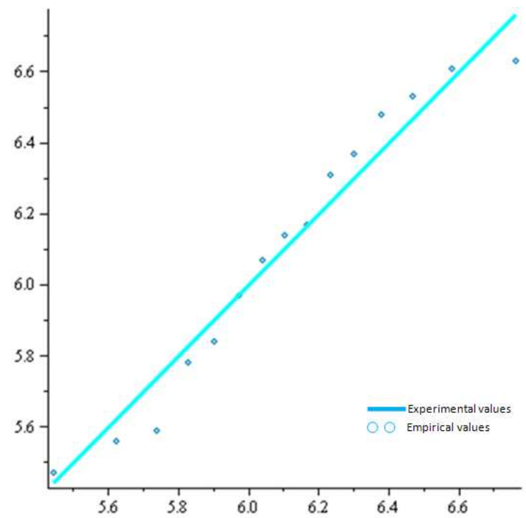

Figure 9. Comparative normal plot for the case 3_linear

3. Conclusions and further aims

Analyzing the above graphs and also comparative plots, some important remarks must be outlined:

- For all the cases, figures 7-9 show that it was done a reliable mathematical model; the computational simulations validate the experimental research since, as it can be seen, the points are very close to the linear path followed by the experimental values.
- This gives rise to consider in more detail the analytical expressions that define the surfaces and to test other values, from analytical but especially experimental standpoint. It is well known how important is to test greater velocities of pressing, for example.
- On the other hand, an immediate aim should be to go further with the mathematical - statistical model associated to the experimental research, to explore new statistical appliances in order to get new tools for validating the experimental research.

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