USING NEURAL NETWORKS IN THE PROCESS OF MIXING HETEROGENEOUS GRANULAR MATERIALS

Alicja Kolasa-Więcek
Department of Economics and Regional Research, Opole University of Technology
Jolanta Królczyk
Agricultural and Forest Engineering Department, Opole University of Technology

Abstract. The article presents an attempt based on experimental data to employ neural network for predicting intermixing ratios for loose materials in a drum mixer. Obtained predicted research results were compared to empirical data using the Pearson's test. Obtained correlation coefficient value is 96%, and proves good data matching.

Key words: granular materials, mixing, drum mixer, neural networks

Introduction

Loose material mixing is a universally used process, which necessarily accompanies man in various economy sectors. Mixing operation is carried out in order to make mix composition homogeneous, that is to distribute mixed materials evenly. The effect may proceed spontaneously (e.g. due to diffusion of particles), or be forced by external factors (e.g. motion - mixer rotation). Mixing process of granular materials characterised by various densities causes a lot of problems due to the influence of many factors at the same time, e.g. parameters of mixed ingredients, mixer type and its parameters, process realisation conditions. Prolonged mixing operation is required to ensure high ingredient intermixing ratio; in practice it is hard to get an ideal mix (100% homogeneity). The measure of attained mixing state is either standard deviation of ingredient mass fractions in a mix or variance..

Research methodology and purpose

The issue of the impact of changes in drum mixer slenderness ratio on the quality of reached intermixing ratios for pairs of loose materials has been researched by the co-author of this work [Kolasa 2002]. Some of the experimentally obtained results have been used in this article, as input data for neural analyses. Data compared in Table 1 was the teaching series.

Table 1. Intermixing ratios for respective parameters of mixer and mixed materials - author's own computations [Kolasa 2002]

Drum diameter	Drum length	Density ratio for materials		
		0.7	1	3.25
		Intermixing ratio for materials		
212	80	0.977	0.98	0.98
	110	0.97	0.977	0.97
	150	0.963	0.97	0.967
	200	0.97	0.967	0.96
425	80	0.97	0.963	0.967
	110	0.956	0.96	0.95
	150	0.946	0.953	0.933
	200	0.936	0.937	0.927
635	80	0.97	0.97	0.96
	110	0.953	0.957	0.94
	150	0.88	0.907	0.88
	200	0.84	0.88	0.847
850	80	0.965	0.967	0.956
	110	0.909	0.943	0.845
	150	0.857	0.92	0.837
	200	0.827	0.84	0.803

A horizontal drum mixer characterised by periodic duty has been used in the research.

On the basis of Rose's definition [Rose 1959], intermixing ratio was computed after each mixing step:

$$M = 1 - \frac{s}{\sigma_0} \tag{1}$$

where:

s – standard deviation of mix composition in *n* samples:

$$s = \sqrt{\frac{\sum (x_i - p)^2}{n}} \tag{2}$$

where:

p – probability of finding a tracer in any segment,

σ_0 – standard deviation in the beginning of mixing process:

$$\sigma_0 = \sqrt{p(1-p)} \tag{3}$$

Mixing step number corresponds to one drum rotation.

Mixed ingredients are binary granular systems (Table 2).

Table 2. Parameters of materials used in the research

Key ingredient	Density ρ_t [kg·m^{-3}]	Density ratio: ρ_t/ρ_r continuous phase ρ_r – 2400 [kg·m^{-3}]
Material 1	7800	3.25
Material 2	2400	1
Material 3	1680	0.7

The purpose of the research was to demonstrate the application potential of an artificial neural network in predicting intermixing ratios for pairs of loose materials.

Artificial intelligence tools seem to be a well-grounded method to use in predicting processes for mixing effects. This method allows free handling of variables (both ingredients and mixer), without carrying out expensive, time-consuming and laborious laboratory or industrial tests. Studies carried out by other scientists prove that owing to their versatility, artificial neural networks are applied in a widening spectrum of agricultural sciences [Mueller, Boniecki, 2006; Koszela, Weres, 2005; Dach et al. 2001].

Mixer length and diameter, and material densities and density ratios were assumed as independent characteristics of teaching vectors. Ingredients intermixing ratio value was the output variable in the examined case. Additional mixer parameters and material density ratio values were taken for prediction studies. The studies were carried out using the Flexible Bayesian Modelling network. In comparison with other networks, it is characteristic for Bayesian networks that they work excellently in situations when there is no *a priori* information available, or the information is limited [Neal 1996], or when the information is obscure [Lampinen, Vehtari 2001]. Bayesian networks are used to demonstrate relations between events in a concise manner and according to the theory of probability. They constitute a subcategory of probabilistic graphical models, called conviction or causal models. A Bayesian network encodes information concerning a specific domain using acyclic directed graph, in which vertexes (nodes) are event equivalents, and arcs are responsible for causal connections between these events.

The teaching set consisted of 48 cases, and the testing set of 120 cases (Fig. 1). A network was built consisting of 3 variables in an input layer, with one hidden layer built of 6 neurons, and an output layer built of 1 neuron. Obtained quality parameters for network learning – including recoil index of 0.2 (for variability boundaries determined within range 0.1-0.3) and trajectory graphs of check values, the so-called weight hyper-parameters of 0.363 (taken for variability boundaries ranging from 0.3 to 0.8), prove correct progress of network learning process (Fig. 1).

```
bash-3.1$ ./bat.mixing
Number of training cases: 48
Number of test cases: 120

Number of realizations: 1  Total points: 1

Mean: 0.200000

Number of realizations: 1  Total points: 100

Mean: 0.363000
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Fig. 1. Network learning parameters

authors' own computations

Research results and their interpretation

Analysis of mixing results obtained by predicting for different geometrical drum dimensions allows generalising that intermixing state obtained for examined pairs of materials ranges from bad (< 0.7) to excellent (> 0.96) [Rose, Robinson 1965]. Examples of prediction results are shown below. Analysed characteristics significantly affect materials intermixing ratio value. Generally, it should be stated that higher density ratio value for mixed granular materials corresponds to lower intermixing ratio value, which is shown e.g. in examples *a* and *b* in Figure 2. Comparison of predicted data in form of 3D diagrams was carried out using the Statictica 9.0 application.

a) b)

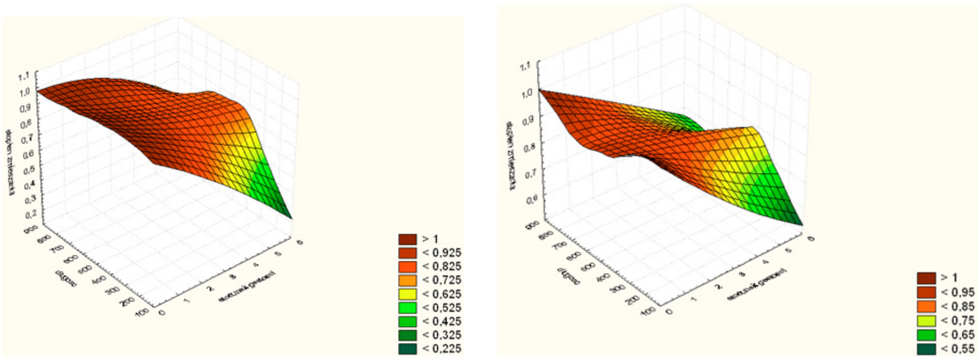


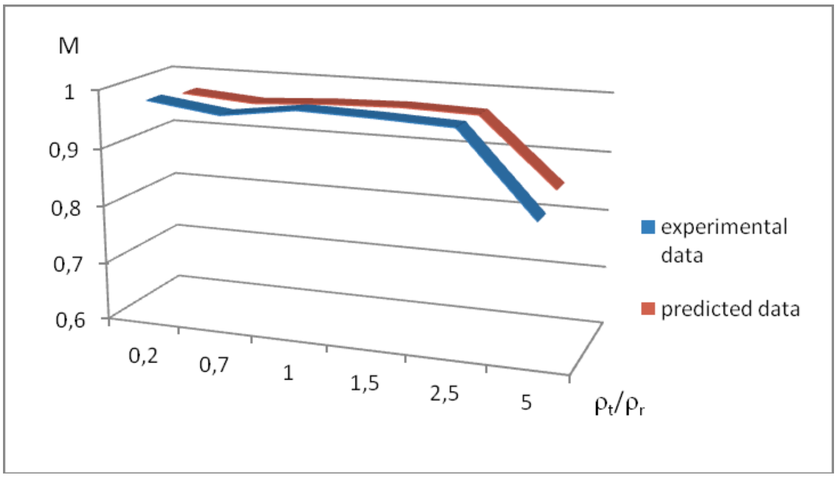
Fig. 2. Example surface diagrams of intermixing ratio relative to materials density ratio and mixer length; for drum diameter: a) D=50 mm; b) D=150 mm;

authors' own computations

Highest intermixing ratio values were obtained for drum length: 50 mm (Fig. 2a). It should be observed that drum parameters have considerable impact on the quality of results. For mixer length exceeding its diameter approximately twice, the researchers observed mix state defined as quite good (0.8-0.9) to excellent, within the whole range of examined pairs of materials.

Fig. 3 compares the results of empirical and neural research. Due to high number of obtained prediction combinations, randomly chosen examples have been shown.

a)



b)

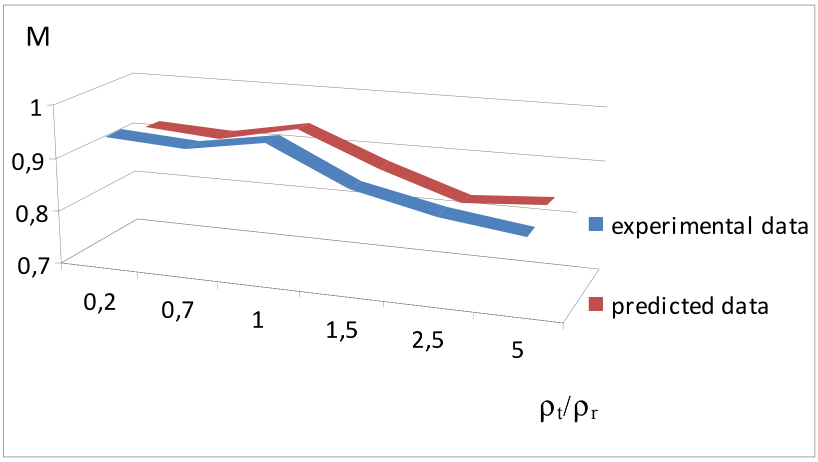


Fig. 3. Comparison of empirical and predicted results; a) L=850 mm, D=50 mm; b) L=635 mm, D=250 mm

authors' own computations

Completed modelling analyses confirm the existence of relations between intermixing ratio values and parameters of mixed ingredients and mixer parameters. Lowest intermixing ratio values were obtained for highest density ratio ρ_t/ρ_r.

Pearson's test was used to evaluate the quality of predicted intermixing ratios relative to the experimental ones. The research was carried out using the R-Project v. 2.10.0 statistical package. Received correlation coefficient value near 0.96 attests very good matching of model data to empirical data (Fig. 4).

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        Pearson's product-moment correlation

data:  dane_eksperyment. and dane_model.
t = 19.4173, df = 30, p-value < 2.2e-16
alternative hypothesis: true correlation is greater than 0
95 percent confidence interval:
 0.9318942 1.0000000
sample estimates:
      cor
0.9624427
```

Fig. 4. Correlation test result for empirical and predicted data

authors' own computations

Conclusions

1. Obtained research results prove that it is possible to use neural networks in predicting intermixing ratios for pairs of granular materials.
2. Completed analyses prove that mixer parameters and density ratio for pairs of loose materials have considerable impact on obtained intermixing ratio values.

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WYKORZYSTANIE SIECI NEURONOWYCH W PROCESIE MIESZANIA NIEJEDNORODNYCH MATERIAŁÓW ZIARNISTYCH

Streszczenie. W artykule na podstawie danych eksperymentalnych dokonano próby zastosowania sieci neuronowej do predykcji stopni zmieszania materiałów sypkich w mieszalniku bębnowym. Uzyskane prognozowane wyniki badań porównano z empirycznymi przy użyciu testu Pearsona. Wartość uzyskanego współczynnika korelacji wynosi 96% i świadczy o dobrym dopasowaniu danych.

Słowa kluczowe: materiały ziarniste, mieszanie, mieszalnik bębnowy, sieci neuronowe

Correspondence address:
Alicja Kolasa-Więcek; e-mail: a.kolasa-wiecek@po.opole.pl
Katedra Ekonomii i Badań Regionalnych
Politechnika Opolska
ul. Waryńskiego 4
45-047 Opole, Poland