Artificial Intelligence as a Decision-making Tool in Planning the Research

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Abstract

The quality of a finite product is influenced both on quantitative and qualitative factors and thus it is somewhat difficult to determine the major factors which affect it and their degree of influence. In this paper we present the usage of artificial intelligence (in particular artificial neural networks) in the development of an efficient research plan for studying the quality of finite products - in particular, wood briquettes obtained from various biomass mixtures.

Keywords: Artificial intelligence, Neural networks, Innovation, Finite products

1. Introduction

There is a strong correlation between basic research and applied research. The linear process linking basic research to applied research, development, commercialization, diffusion and their consequences is commonly denoted as technological innovation and development (Zahra et al, 2007). During the last century, innovation became gradually the most important factor leading to productivity growth. Consequently, one cannot omit the role of academic research and its applications in the socio-cultural and economic development. Thus, new strategies to create wealth by valorizing existent results of academic research were developed.

Once agreed on the importance of research (both basic and applied) for technological development and, ultimately, for gaining wealth, it becomes simple for a company to search for new solutions and improvements regarding their products in the academic environment. Thereby, real-life processes and phenomena are modeled and the subsequent physical, chemical or mathematical models are studied for their properties.

Development of computers and computer science lead to new methods to analyze a model. While methods of numerical analysis existed since more than 2000 years, the speed performances of modern computers lead to numerical solutions of increasingly complex problems, from numerical weather prediction to programming automatic pilots and even chemical properties of semiconductors.

All the models mentioned above use quantitative input values in order to compute quantitative, numerical outputs. A problem arises when, during the modeling phase, qualitative (discreet) inputs are required. The classical models should be replaced by new, statistical models, created either by statistical methods or by using artificial intelligence tools.

Our work is a response to the need of innovation expressed by a private company, SC Andrei Slavici SRL. The company is searching for innovation in the production of wood pellets and briquettes on the market of nonconventional bio-fuels. There is a positive global trend in the usage of renewable sources of energy and Romania has already overcome the 22% threshold of renewable energy used, assumed for 2020 (REN 2015). In this regard, economic, environmental and political aspects of using biomass in energy are investigated worldwide (Davis 2014, Nishiguchi 2016), and especially the usage of wood pellets as solid biofuel (Grammelis 2010).

2. Methods

Every research activity contains a data collection phase. Data collection ensures there is enough real life information to construct a model and / or to set its limits. Data may refer to (Maris 2013, Greer 2015, Untaru 2012):

- physical or chemical properties of an object (such as density, thermal conductivity, melting point, etc.)
- biological models (e.g., "artificial" neurons used to model "real" neurons)
- initial values for a process when dealing with time-progressive models (such as initial temperature, initial concentration, etc.)
- boundary values for an object or process (such as temperature on the edges of the studied object, velocity of the edges, etc.)
- economic information (prices, productivity, demand and offer, etc.)
- miscellanea (state of economy, amount of rain, client's degree of satisfaction, provenience of the object, availability of the object in a specific area, etc.)

The traditional statistical methods used to link a certain output variable given a set of input conditions are generically denoted by the term of "curve fitting". Among them, one of the most commonly used statistical methods is the least squares method.

New techniques of forecasting were developed as consequence to the development of computers and Artificial Intelligence. Instead of "curve fitting", the term "pattern recognition" appeared, designating a process through which a label is assigned to a given input value.

Among the pattern recognition software currently used in the field of decision making, there are (knowledge-based) expert systems and artificial neural networks (ANNs).

Expert systems emulate a real expert. Hence, the output obtained using an expert system is comparable to a decision of a most competent real expert (Corvid Exsys). However, no decision could be made in the absence of the knowledge base. Usually, the knowledge base is a collection of rules with the general form "IF condition THEN result." The process of decision making is based on the rules previously loaded in the knowledge base, leading to an answer to the problem (question) in discussion.

ANNs became widely used since 1980s. The "neurons" of an ANN are software elements which emulate human neurons by processing some input data and returning a function of it. Currently, ANNs are considered as one of the most accurate decision-making tools. ANNs overcome the restrictions of classical methods used for complex problem solving like forecasting electricity consumption (Kaytez et al., 2015), forecasting wind power and control the parameters of wind turbines (Ata, 2015), analysis of consumer choices (Kennedy at al., 2016) and estimating gross calorific values (Estiati et al., 2016).

To use an ANN, one should go through three phases (Russell and Norvig 2002):

- the training phase (during which known associations between inputs and outputs are fed into the network);
- the validation phase (during which the outputs of the ANN are validated against known values of the outputs);
- the testing phase (in which the ANN predicts outputs associated to a certain set of inputs).

Since ANNs are generally more accurate than expert systems, linking both quantitative and qualitative inputs in order to obtain an output, we will use ANNs to achieve our goals.

A typical ANN contains (Figure 1):

- an input layer – I, composed of a certain number of neurons,
- one or more hidden layers – H (each composed of a certain number of neurons)
- an output layer – O, usually composed of one neuron (the "answer" of the network).

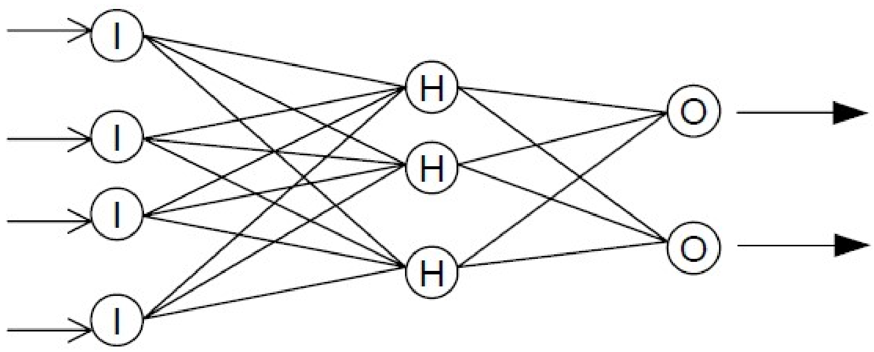

Figure 1. Example of multilayer neural network (source: Samarasinghe, 2016)

The computations were made using the Neural Networks toolbox of Matlab (Chapman, 2015).

3. Case study

Our research started with a request from the company SC Andrei Slavici SRL to help innovate their production.

A private microenterprise, SC Andrei Slavici SRL was founded in 2012 as a spin-out of the Ioan Slavici Foundation for Culture and Education. Its purpose is to capitalize commercially the results of scientific research. The NACE code of the company is 1629 (Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials), which allows the company to produce fire logs (briquettes) and fire pellets out of pressed wood or substitute materials. The technological line of the company allows the processing of a minimum of 400 kg raw material at once. The company search innovation in order to produce fire pellets and briquettes with higher energetic efficiency, addressing thus to the growing market of nonconventional bio-fuels. A more detailed description of the situation was given by Maris et al. (2016).

The key process parameters of pelletization have been listed by Stelte in 2014: wood species (chemical composition), particle size, content of moisture, conditioning temperature, pelletizer temperature, length and diameter of the die, rotation speed of the die and, in case of torrefied biomass, the degree of torrefaction. Other important aspects of the problem are the chemical composition of the resulting ash (Biedermann and Obernberger, 2005), as it can damage the stoves, and ash melting temperature, a higher temperature meaning a more efficient combustion (Holubick et al, 2015). In addition to these aspects, the price of raw material should not be neglected, as it affects the price of the finite product and hence its attractiveness to customers. The price of raw material depends on demand/offer ratio, frequency of cataclysms, state of economy, etc. (Untaru et al, 2012)

For the moment, the chemical composition of certain wood types will be considered. The chemical composition is known (Krajnc, 2015) and will be used further in the computations. Using the Mendeleev formula, the total calorific value can be computed for various combinations of wood. An example of these values can be found in Table 1. However, while the Mendeleev formula links the calorific value of the fuel to only 4 chemical components, we aim to feed the neural network with an extended chemical composition of the fuel (10 chemical components).

Table 1. Calorific values for various types of wood and combinations of woods (sample)

Biofuel	**C**	**H**	**O**	**S**	**Calorific value (Mendeleev formula)**
unit	*(%,wt. cont.)*	*(%,wt. cont.)*	*(%,wt. cont.)*	*(%,wt. cont.)*	*(MJ/kg)*
Bark	51.400	5.700	38.700	0.085	19.081
Beech	47.900	6.200	43.300	0.015	17.693
Poplar	47.500	6.200	44.100	0.031	17.679
Spruce	49.800	6.300	43.200	0.015	18.658
Willow	47.100	6.100	44.200	0.045	17.420
Beech and Spruce 1:1	48.850	6.250	43.250	0.015	18.279
Spruce and Beech 2:1	48.850	6.250	43.250	0.015	18.405
Beech and Spruce 2:1	48.850	6.250	43.250	0.015	18.152

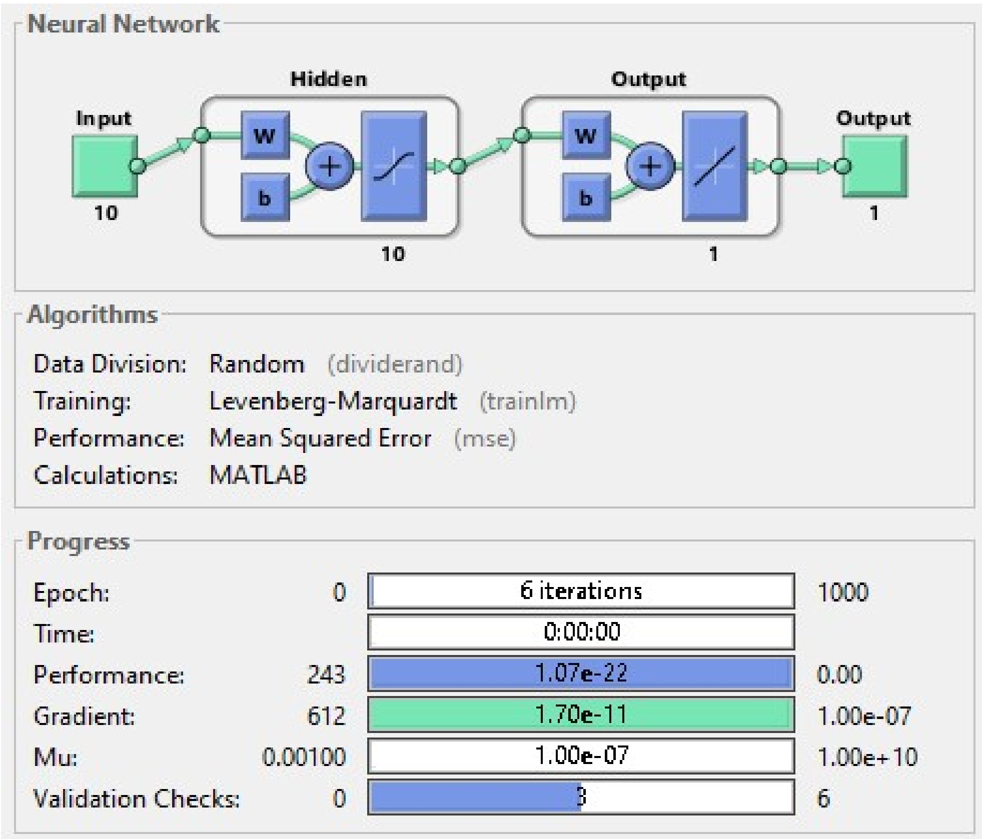

Figure 2. ANN structure and performance

For our purpose, we used 27 samples, each sample containing 10 different elements, referring to unmixed wood. The set was divided randomly in training set (70% of the sets of values, i.e. 19 sets), validation set (15% of the sets of values, corresponding to 4 sets) and testing set (15% of the sets of values, corresponding to 4 sets).

The data division was performed randomly. The best fitting results were obtained when training the ANN using Levenberg-Marquardt algorithm, corresponding to an overall accuracy of 99.57%.

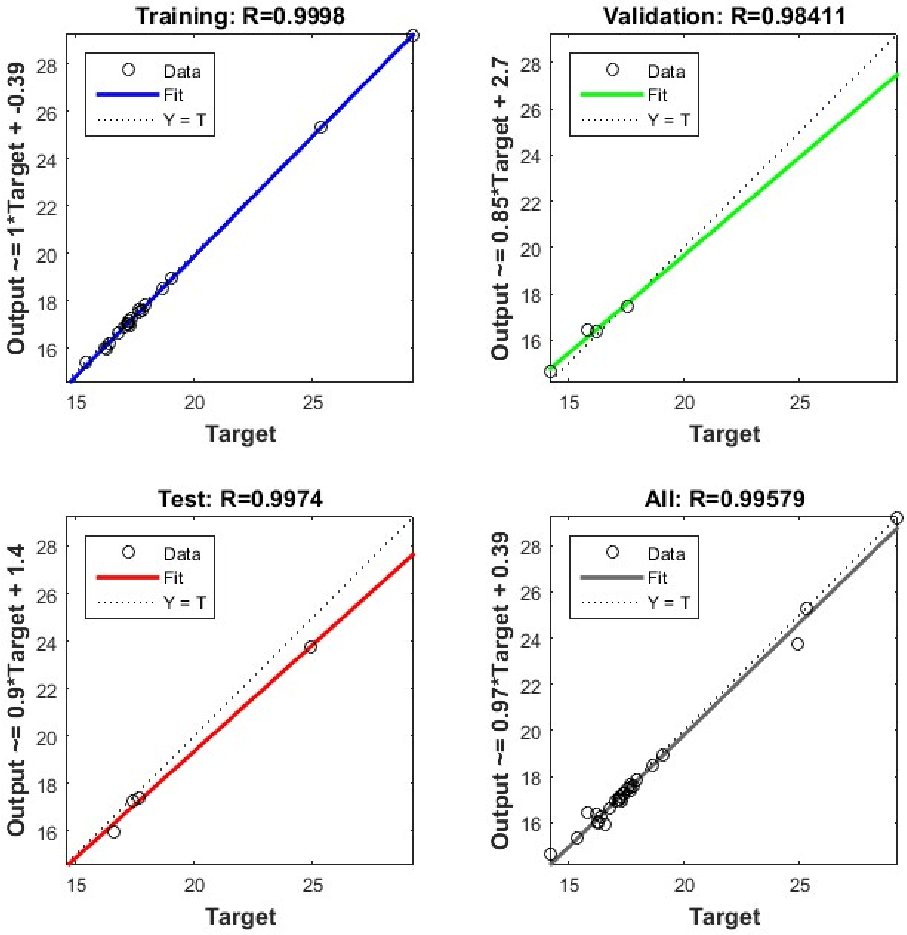

Figure 3. Regression plots for the case presented

Table 2. Comparison of the calorific values obtained by using the Mendeleev formula and the ANN (sample)

Biofuel	**Real calorific value (Hartmann et al, 2013)**	**Calorific value Mendeleev formula (4 chemical components)**	**Calorific value ANN (10 chemical components)**
unit	*(MJ/kg)*	*(MJ/kg)*	*(MJ/kg)*
Bark	19.200	19.081	18.9322
Beech	18.400	17.693	17.4034
Poplar	18.500	17.679	17.5016
Spruce	18.800	18.658	18.5133
Willow	18.400	17.420	17.2842
Beech and Spruce 1:1	-	18.279	17.9313
Spruce and Beech 2:1	-	18.405	18.1186
Beech and Spruce 2:1	-	18.152	17.7503

The calorific value computed by the ANN (based on 10 inputs) is generally less than the calorific value computed by Mendeleev formula (based on 4 inputs).

As further work, the inputs will consider the rest of the influencing parameters, and the outputs of the neural network will also contain the amount of noxious by-products and the price of the finite product.

The performance of an ANN is influenced both by its architecture and the algorithms used during the computations. While it is important to find the best combination of architecture and algorithms, it is not practical to perform this experiment even using the newest computation resources. Thus, in order to optimize the ANN, one should determine first the network parameters with the greatest influence on the forecast accuracy. Once these parameters are determined, statistical methods should be used to construct a response surface in order to determine the best values for the influencing parameters. (Slavici 2006) However, as this represents work in progress, these results should be presented in another paper.

The results obtained using ANNs are useful to discern which inputs (and with what weights) determine the desired outputs. This is useful because it will help to perform the required practical experiments with reduced costs.

4. Conclusions

Artificial Intelligence provides the researcher with versatile tools, which can be successfully used in the process of planning the research.

ANNs can be successfully used to estimate the yield of a certain combination of inputs in a given situation, despite some practical problems such as: a high complexity of the mathematical model for the required situation, associated with an insufficient accuracy of this model; incomplete available data, affected by noise and bias; too many restrictions to be applied and simultaneously optimized in the process. Moreover, they allow the researcher to process both quantitative and qualitative data.

Currently, we constructed an ANN to process the inputs associated to the fabrication of wood pellets and briquettes. As input, it was considered only the chemical composition of the biomass, the output being the net calorific value. The overall accuracy of the network was 99.57%. As a further work, the inputs will be diversified and the ANN will be optimized, thus leading to more accurate forecasts.

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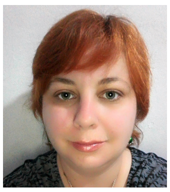

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