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COMPARATIVE ASSESSMENT BY NEURAL NETWORKS MODELING

Cezarina Afteni[1], Gabriel Frumuşanu[1]

Department of Manufacturing Engineering, "Dunărea de Jos" University of Galaţi, România
Cezarina.Afteni@ugal.ro

ABSTRACT

Current manufacturing industries are experiencing a paradigm shift towards more flexibility to respond quickly and efficiently to constant changing customers requirements, new technologies and increasing product variety. In today's manufacturing environment it is necessary to make diverse decisions, which mainly concern to all stages of the manufacturing activity: bidding, negotiating, order acceptance, product design, processes planning and jobs scheduling. The decision consists in selecting the most suitable alternative from the potential ones, therefore a comparative assessment of the potential alternatives is required. In this paper we present a different approach to performing the comparative assessment, based on modeling with neural networks. Neural networks are used for establishing the dependence relations between the key process parameters and measured datasets e.g. cost, time span, consumed energy etc. A numerical simulation for comparative assessment by modeling with neural networks, with the help of an instances artificial database is also presented.

KEYWORDS: comparative assessment, modeling, neural network, instances database.

1. INTRODUCTION

In a technological world marked by the exacerbation of competitive struggles, there is no place for manufacturing processes that ignore the requirements of competitiveness and, implicitly, intrinsic process performance to sustain this competitiveness.

The companies define and implement strategies to develop products and production processes through which they obtain products of superior quality compared to their main competitors at the lowest manufacturing costs.

In today's manufacturing environment it is necessary to make diverse decisions, which mainly concern to all stages of the manufacturing activity: bidding, negotiating, order acceptance, product design, processes planning and jobs scheduling. The decision consists in selecting the most suitable alternative from the potential ones, therefore a comparative assessment of the potential alternatives is required. The selection is made after given criterion (e.g. cost, time span, consumed energy etc.), is made after in connection with a features of potential alternatives whose value is not necessarily known. This selection requires comparative assessment, which aims to establish a relation of order over potential alternatives set. From the analysis of the published papers, it can be pointed out that the usual method underpinning the comparative assessment supposes the direct, separate evaluation of feature value for each alternative, before decision-making.

For example, in paper [1] the authors propose a method to control which includes the modeling of cost and time, these being two very important elements of MTO manufacturing process performance criteria, from customer enquiry up to product delivery. Therefore, in their paper, the cost and time will be estimated by a set of appropriate three techniques which are based on analytical modeling, neural modeling, or *k*-nearest neighbor regression (*k*-NN). The authors affirm, that in practice, decisions on order acceptance and on production planning are often made separately. Sales department is responsible for accepting orders, while the production department is in charge of production planning for implementation of accepted orders.

The method proposed in their paper aims to facilitate the connection between the two departments by an integrated control based on the earning power evaluation.

In this paper we present a different approach to perform the comparative assessment based on the modeling with neural networks. Neural networks are used to modeling the relation between the values of some output sizes, these representing dimensions that characterize the performance of the manufacturing process (effect parameters) e.g. cost, time span, consumed energy etc. and the variables that describe the manufacturing process as a causal factor (cause parameters) e.g. length, diameter, accuracy, material, rigidity etc. The values of the cause parameters and the effect parameters corresponding to them, based on which the modeling is done, are extracted from the instances database, by referring them to past cases recorded.

This approach enables companies to collect, process, transmit and provide faster the necessary data on cost, time and energy consumption when a customer order is received, or in the case of a call for tender when the response time can represent an advantage over competitors.

For example, in the case of complex industrial processes such as the mechanical processing of a product involving the transfer of the half-finished product to a standard tehnological flow or alternative technological flows, in the decision selection must take into account the technical-economic indicators such as: the costs, the processing time, the energy consumption, number of staff required, flow continuity, and availability of equipments and assets for each technological flow.

The rest of the paper is organized as follows: the next section presents the study of applying neural networks in the modeling of manufacturing process. The third section defines the concept of comparative assessment based on the modeling with neural networks. The fourth section deals with a numerical simulation of method application, performed on an artificial database. The final section is dedicated to conclusion.

2. NEURAL NETWORKS APPLIED IN MANUFACTURING PROCESSES MODELING

This section presents some of the existing researches on the application of neural networks in manufacturing process modeling.

In present, special attention is paid to modeling and simulation with neural networks for applications in manufacturing process.

The neural modeling is a concept widely used in theoretical research, but it is at the beginning of the road in the practical areas.

Neural networks are systems that can acquire, store, and utilize knowledge gained from experience [2].

Artificial neural networks, represent artificial intelligence systems created with an aim to imitate functions of human brain and biological neurons and to be applied in solving different problems which require performing of complex operations.

This kind of networks "Figure 1" is composed of several calculations unites called neurons, which are combined in layers and operating in parallel. The information will be propagated layer to layer, from the input layer to the output layer. The ANN have the ability to store empirical knowledge and make it available for the users [3].

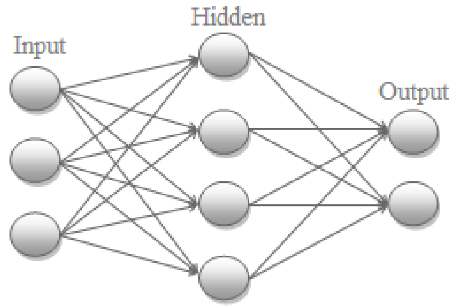

Fig. 1. *Artificial neural network [3]*

The input layer consists of neurons that receive input from the external environment. The output layer consists of neurons that communicate the output of the system to the user or external to the environment. There are usually a number of hidden layers between these two layers. The hidden layer of an ANN model acts as a black box to link the relationship between input and output [4].

There are many researches in which neural networks were used for supporting the selection made after a given criterion such as:

- the costs;
- the time span;
- the energy consumption.

For example, if the the criterion is *the energy consumption* (CE), in paper [5] a real machining experiment is referred to investigate the capability of artificial neural network model for predicting the value of energy consumption. For develop predictive model was using Artificial Neural Network (ANN) technique, used the experimental data of cutting energy, during milling of medium carbon steel. The machining parameters were spindle speed (n), feed rate (f), depth of cut (a_p) and width of cut (a_e). After a number of trials, the neural network structure is 4-9-2, leads to best result and it consists of:

- in input layer coresponding to four machining parameters: n, f, a_p, a_e;
- one hidden layer with nine neurons;
- one output neuron in output layer (CE).

In Figure 2 and Figure 3 is shown the performance of the developed network on the basis of correlation coefficient (R value) between the output values and the target values for the test data (5) and entire data (27).

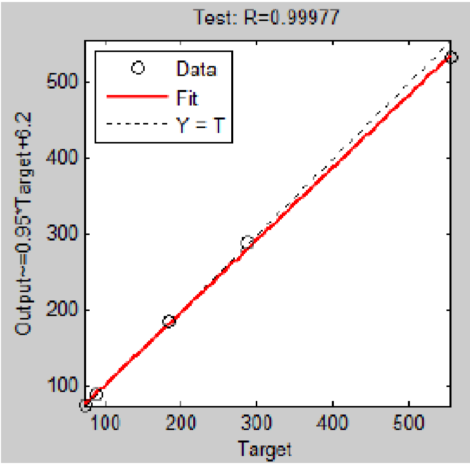

Fig. 2. *Correlation between the predicted values and test data [5]*

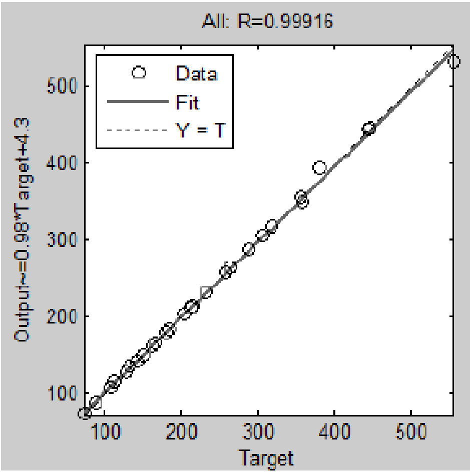

Fig. 3. *Correlation between the predicted values and entire data [5]*

The R value is a measure of how closely the variation in output is explained by the targets. It lies in between 0 and 1. If it is 1 then it indicates the perfect correlation between the target values and output. Correlation coefficient of 0.99 was obtained between the entire data set (experimental data) and model predicted values which indicate good correlation.

In [6] it is presented an approach to automate the application of analytical models to manufacturing problems. The authors describes a case study that focuses on predicting the energy consumed corresponding to the machines operational parameters such as: feed rate, spindle speed, and depth of cut, in the case of a milling machine tool. A milling machine tool obviously involves more parameters, for simplicity, the authors decided to only keep these three parameters have the biggest impact on the energy consumption in the milling process. In addition, they present an algorithm to generate a predictive model from an neural networks and available data. In their example, the neural network is composed of:

- an input layer, represented by the three input parameters:
  - feed rate: the velocity at which the tool is fed;
  - spindle speed: rotational speed of the tool
  - depth of cut: the actual depth of material that the tool is removing.
- a hidden layer are used to represent the relationships between the input layer;
- the output layer contains the output neuron that represents the predicted energy in their study.

A feed-forward neural network that represents our use case is illustrated in Figure 4.

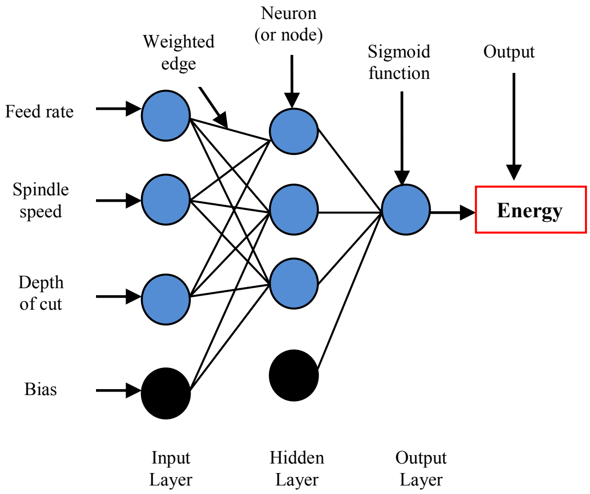

Fig. 4. *Neural network [6]*

When the criterion is *the time*, I. K. Praszkiewicz [7] develops a new method for time per unit determination by application of neural networks in small lot production in machining. She presents a set of features considered as input vector and time consumption in manufacturing process and treated as output of the neural networks. The paper [8] presents an approach to solving the problem of machining time estimation in real manufacturing of complex production within CNC machining systems.
The autors used heuristic analysis of the process for define the attributes of influence to machining time.

For the problem of estimating machining time the authors following „Neural Computing techniques" are used: Back-Propagation Neural Network, Modular Neural Network, Radial Basis Function Neural Network, General Regression Neural Network and Self-Organizing Map Neural Network.

The best results in the validation phase were achieved by Modular Neural Network (RMSE: 1.89%) and Back-Propagation Neural Network (RMSE: 2.03%) while the worst results were achieved by Self-Organizing Map Neural Network (RMSE: 10.05%).

If the criterion is *the cost*, in [9] J. Park et al. develop an approximate method for the estimation of maintenance cost (MC) as one component of life-cycle cost (LCC). This method allows the designer to make a comparative estimation of maintenance cost for design alternatives by considering high-level product attributes and the maintenance cost during the life cycle of products. To estimate the maintenance cost, the identified product attributes are used as inputs and the calculated maintenance cost is used as outputs in a learning algorithm based on artificial neural networks. An artificial neural network (ANN) is trained on product attributes and the MC calculated from historical maintenance data.

In [10] a cost model development process is described and a novel cost modeling technology artificial neural networks (ANN) is developed. The author to undertaken a series of experiments to select an appropriate network structure for estimating the cost within the production network. In the final he the model is validated through a case study.

In this paper, the neural networks are used to establish the relation between the cause parameters that describe how the process performs such as lenght, diameter, accuracy, material, rigidity etc. and the effect parameters that describe the process results such as cost, time span, consumed energy etc.

3. COMPARATIVE ASSESSMENT PROBLEM

The comparative assessment is used to choose the best alternative in order to solve a manufacturing problem.

In our opinion, we consider that the most relevant information about a manufacturing process provides a database are recorded in which both the cause parameter values and the resultant effect parameters, from previous similar manufacturing processes.

In order to perform a comparative assessment between more variants, in the situation where the values of the descriptors parameters of the manufacturing processes are not identical in the database, it is necessary to make an estimate of the database value of the results by modeling.

The current approach of comparative assessment is accomplished by comparing the rankings of addressed alternatives. The ranking of a given alternative is assigned by measuring the distance between its cause-variables values and the ones corresponding to the pivot of a neighborhood selected from past instances database. The distances are evaluated by using neural networks modeling.

Paper [11] presents a solution of comparative assessment, based on alternatives rankings to potential alternatives, by referring them to the cases of already performed manufacturing activities, recorded as past instances database, after ranking criteria such as cost, time span, consumed energy etc. In the paper, the selection decision results by comparing of potential alternatives rankings. For finding the ranking of a given alternative, a solution to assess the difference between instances is needed, at first. Then, after iteratively defining instances neighborhoods from database and modeling them by multiple nonlinear regression, its ranking is determined. Here, we propose an expression for the distance-function together with an algorithm for actually finding the ranking of the analyzed alternative. At the end of the paper, there is a numerical simulation for the instance-based comparative assessment, performed with the help of an artificial instances database.

In this paper, the modeling is done with the help of neural networks, for each set of input data, on a neighborhood of their values. The neighbors may be different for each of the cases we want to compare, so we will have different patterns.

4. ALGORITHM OF THE METHOD

The algorithm for modeling with neural network consists in several stages:

- the current case is defined through its cause-variables values x, y and z, while its result T is unknown. In these conditions the instances database means a recorded set of n lines:

$$\{(x_k, y_k, z_k, T_k) |\ k = 1 \dots n\} \tag{1}$$

where result values T_k, obtained for given values of cause-variables x_k, y_k and z_k, are known (e.g. by measurement).

- the values of variables recorded in database are separately scaled on columns, hence:

$$x_k, y_k, z_k, T_k \in [0,1], \forall k = 1 \dots n. \tag{2}$$

- the *current case* (x, y, z), can be grouped around a *pivot-case* (x_v, y_v, z_v, T_v), hence forming a neighborhood of it.
- the specific combination of windows are defined:

$$|x_k - x_v| + |y_k - y_v| + |z_k - z_v| < \varepsilon, \forall k = 1 \dots \tag{3}$$

- the coordinates differences (dx_j, dy_j, dz_j, dT_j) are calculated for each of the n_i cases (x_j, y_j, z_j, T_j) from N_i:

$$\begin{cases} dx_j = x_j - x_v \\ dy_j = y_j - y_v \\ dz_j = z_j - z_v \\ dT_j = T_j - T_v \end{cases} \tag{4}$$

- the relation between dT, on one side and dx, dy and dz, on the other side, is modeled by *neural networks*:

$$dT = f(dx, dy, dz) \tag{5}$$

- the values of Δx , Δy and Δz are calculated:

$$\begin{cases} \Delta x = x - x_v \\ \Delta y = y - y_v \\ \Delta z = z - z_v \end{cases} \quad (6)$$

- the resulted value of ΔT are calculated:

$$T = T_V + \Delta T \quad (7)$$

- the case ranking is finded.

5. NUMERICAL SIMULATION

This section presents a numerical simulation on an artificial instances database, for the implementation of developed solution by modeling with neural networks.

The present case of comparative assessment by modeling with neural networks addresses the problem defined through three cause-variables x, y and z, while its result T is unknown.

The database it composed of four columns:

- first three for *x*, *y*, and *z* cause-variables;
- the last for result-variable, *T*;
- $n = 150$ lines.

The values of result-variable were calculated with relation:

$$T(x, y, z) = 2 \cdot x^3 + 3 \cdot y^2 + 2.5 \cdot z + 0.5 \quad (8)$$

The values for each cause-variable were considered as a non-uniform division of [0, 1] interval, in random succession.

The values for result variable were scaled such as they also belong to [0, 1] interval.

5.1. *Case ranking assignment*

We supposed the current case ($x_1 = 0.6$, $y_1 = 0.2$, $z_1 = 0.7$), needing to be ranked relative to the instances database from above. At first, the pivot ($x_{v1} = 0.58889$, $y_{v1} = 0.18333$, $z_{v1} = 0.72859$, $T_{v1} = 0.35724$) has been chosen from instances database. The modeling by neural networks has been performed in MatLab (*Optimization tools* package).

The values for ε parameter have been selected at each iteration such as the current case neighborhood includes the same number of cases (here, 25 cases). The algorithm for case ranking assignment has been iteratively run. The obtained value is $\Delta T_1 = -0.21285$, hereby $T_1 = 0.14439$ and considered case ranking is $R_1 = 88$.

In Figure 7 is shown the performance of the developed network on the basis of correlation coefficient (R value) between the output values and the target values for the test data.

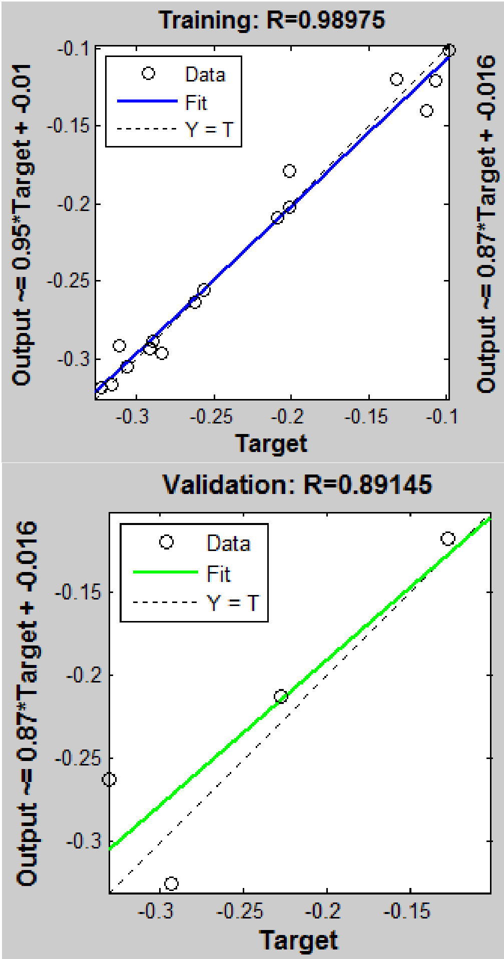

Fig. 7. *Regression plot of Neural Network*

5.2. *Comparative assessment*

In order to sample the comparative assessment based on case ranking, let us consider two different current cases: first is the one addressed in previous section, while second is ($x_2 = 0.25$, $y_2 = 0.15$, $z_2 = 0.45$). One has to choose from the two cases the one having the smallest value of *T* result.

The algorithm for case ranking assignment is applied once again, for second potential case, to which the pivot ($x_{v2} = 0.26296$, $y_{v2} = 0.13333$, $z_{v2} = 0.44271$, $T_{v2} = 0.16722$) is associated from the same instances database. In the same manner as above, we find $\Delta T_2 = -0.15216$, $T_2 = 0.01506$ and case ranking is $R_2 = 26$.

In conditions of the addressed problem, we have $R_2 < R_1$ hence second case must be taken.

6. CONCLUSIONS

At the end of research presented in this paper, our conclusions are summarized as follows:

This paper presents a different approach to perform the comparative assessment, based on modeling with neural networks.

Comparative assessment is accomplished by comparing the rankings of addressed alternatives.

The ranking of a given alternative is assigned by measuring the distance between its cause-variables values and the ones corresponding to the pivot of a neighborhood selected from past instances database.

The distances are evaluated by using neural networks modeling.

We have validated the feasibility of the approach by numerical simulation on an artificial database.

The instance-based comparative assessment enables to make the difference between the analyzed cases with a minimum of both initial information and computational effort.

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